TSINGHUA SCIENCE AND TECHNOLOGY
ISSN 1007-0214 01/13 pp791–799
DOI: 10.26599/TST.2020.9010034
Volume 26, Number 6, December 2021

Towards Rehabilitation at Home After Total Knee Replacement

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Abstract: In this paper, we present the design and implementation of an avatar-based interactive system that facilitates rehabilitation for people who have received total knee replacement surgeries. The system empowers patients to carry out exercises prescribed by a clinician at the home settings more effectively. Our system helps improve accountability for both patients and clinicians. The primary sensing modality is the Microsoft Kinect sensor, which is a depth camera that comes with a Software Development Kit (SDK). The SDK provides access to 3-dimensional skeleton joint positions to software developers, which significantly reduces the challenges in developing accurate motion tracking systems, especially for use at home. However, the Kinect sensor is not well-equipped to track foot orientation and its subtle movements. To overcome this issue, we augment the system with a commercial off-the-shelf Inertial Measurement Unit (IMU). The two sensing modalities are integrated where the Kinect serves as the primary sensing modality and the IMU is used for exercises where Kinect fails to produce accurate measurement. In this pilot study, we experiment with four rehabilitation exercises, namely, quad set, side-lying hip abduction, straight raise leg, and ankle pump. The Kinect is used to assess the first three exercises, and the IMU is used to assess the ankle pump exercise.

Key words: rehabilitation; physical therapy; total knee replacement; avatar; virtual reality; repetition count; range of motion

1 Introduction

As people are living longer and wish to enjoy active living styles, more people are doing hip, knee, and shoulder replacement surgeries. For example, in Jan. 2000, the rate of Total Knee Replacement (TKR) was at 6.0 per 1000 for people that received medicare benefit in the United States. By June 2005, the rate had increased by 48% to 8.8 per 1000[1]. As of 2012, approximately 600 000 people received total knee arthroplasty (including both replacement and reconstruction) surgeries per year[2]. A person might be temporarily disabled due to knee, hip, and shoulder replacement surgeries. A proper and speedy recovery from these surgeries and injuries would not only reduce the medical care cost, but also reduce the suffering of the patients.

Physical therapy is an important method to help achieve proper and speedy recovery for patients who suffered injuries and have recently gone through surgeries such as TKR[3]. In physical therapy, a rehabilitation program consisting of a specific set of physical exercises that is prescribed for each patient. For such a rehabilitative program to be effective, it typically requires many repetitions of each exercise and all of which must be performed correctly[4]. Hence, it is much more desirable to practice at the convenience of home provided that there is portable and low-cost system that

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Manuscript received: 2020-08-08; accepted: 2020-09-08

could provide intuitive guidance and reliable realtime feedback to the patient.

In recently years, we have seen improvements in the current state of practice, such as offering videos for the patient to view at home. Although video-based guidance is much more helpful than the paper-based instructions for the patient to carry out the prescribed exercises correctly, providing video-based guidance is inadequate to inform a patient whether or not he/she has performed the exercise correctly. The state of the practice in rehabilitation care can be significantly improved with an easy-to-use, inexpensive, interactive, and portable system, which can be quickly programmed by clinicians and distributed to millions of patients.

This paper makes the following research contributions:

• We present a study on the feasibility of using Microsoft Kinect version 2 to build a system for TKR rehabilitation at home. We concluded that although Kinect can be used reliably to assess the knee movements, it is incapable of accurately tracking the movements of ankles.

• We address this issue by integrating with commercial inertial sensors to capture and assess ankle movements. We show that with proper filtering of the data collected, the system is capable of reliably assessing the patient movements for TKR rehabilitation at home.

• The system presents a virtual reality interface to the patient with an avatar to demonstrate the correct movements and to mirror the patient's movement with real-time feedback, including the repetition count and range of motion information.

2 Related Work

Since Microsoft released the Kinect sensor in 2010, it has become the most popular vision-based sensor for motion tracking[5–8]. It can be attributed to its low cost (about 100 dollars) and excellent software development support with a free software development kit that can output 3-dimensional skeleton joint positions fairly accurately[9]. Previously, we developed a Kinect-based interactive system for general rehabilitation at home[10, 11]. We also formulated a rule-based framework for describing well-known physical exercises with respect to clinical requirements and how to carry out automated assessment in real-time[12]. We further extended the work to track potentially injury-inducing movements (such as bending, which could lead to lower back pain) of nursing aids working at nursing homes to encourage best practices in patient handling[13–15]. Naturally, the current work for TKR rehabilitation will be based on our previous work. As we will show in the next section, the Kinect sensor could not accurately track the foot movements. Hence, we resort to the use of an inertial sensor to capture the foot movements.

The literature on objective assessment of patient movements using wearable sensors such as inertial sensors for the purpose of rehabilitation has been abundant[16, 17]. We are aware of several works that are directly on TKR rehabilitation[18–21]. However, such systems are typically developed for use in a clinical setting without any intuitive interface for patients. On the contrary, our system presents a virtual reality environment with a virtual avatar that demonstrates the correct way of doing each prescribe exercise, shows the actual movements done by the patient, and displays the repetition count and range of motion.

The value of presenting a virtual reality interface has been confirmed by a number of studies[22–24]. It is generally recognized that such an environment would be more engaging and the clinical outcome for the rehabilitation programs is improved. We hypothesize that the reason for the better outcome is due to a more visually appealing interface, easier-to-follow visual instructions, more interesting program content (such as via a game setting), and real-time feedback (such as the repetition count, range of motion, and quality scores).

Because the exercises for TKR are well-understood and well-defined, the rule-based approach that we previously proposed[12] is a good fit for automated assessment in real-time. Another popular approach is to use machine-learning algorithms to automatically assess the quality of the movements and provide an overall score to the user[25]. Here we briefly summarize the rule-based framework and the mechanism used to dynamically track the movements (including doing repetition count). The fundamental concept for the rule-based framework is that an exercise can be defined in terms of references configurations[11, 12]. The dynamic movements of an exercise are defined in terms of a sequence of key poses, which correspond to key frames in the context of video-based motion tracking. Some exercises require certain body segment to remain stationary, which is defined by a static rule. Many exercises have specific requirements that one must observe throughout the entire repetition, such as the knee should be straight. Such requirements are defined in terms of invariance rules. All rules are defined in eXtensible Markup Language (XML) for extensibility and for readability. Most rules are defined in terms of joint angles, but some are defined in terms of joint displacements, or restrictions of movements within certain anatomical planes.

The mechanism used for the actual movement recognition is based on the finite state machine model[11, 12]. Each state corresponds to a key reference configuration as defined in the dynamic rule. During each repetition, the patient is expected to move from one state to another. At any state, the patient may choose to move back to the initial state (i.e., the initial pose in an exercise). By recognizing the state transitions, we can reliably perform repetition count.

3 Avatar-Based System for Total Knee Replacement Rehabilitation

In this section, we first describe the four exercises for TKR rehabilitation in terms of the requirements in natural language, then we report the feasibility investigation on using Kinect-based system for automated tracking of these exercises, and finally, we elaborate the integration with Inertial Measurement Unit (IMU). We translate the requirements into the rule-based expressions for the first three exercises.

3.1 TKR exercises

We experimented with four different exercises: (1) quad set; (2) side-lying hip abduction; (3) straight leg raise; and (4) ankle pump. The description and the measurements required for each exercise are provided below.

(1) Quad set. The essence of this exercise is for the patient to practice the lifting of his/her each knee gently as much as possible from the straight position. More specifically, the patient is expected to first lay on the ground or the bed with leg straight. At this initial position, the patient should tighten the quadriceps muscle on the front of the thigh and imagine pressing the back of the knee down into the support surface. Then, the patient should attempt to slightly lift the heel off the floor while flexing the knee. The measurement will be focused on the knee angle, that is, the angle formed between the upper and lower legs.

(2) Side-lying hip abduction. The essence of this exercise is to practice lifting the entire leg sideway while lying down. More specifically, the patient is expected to first lie on one side with top leg straight. The patient may bend bottom knee for support. Then, the patient should raise top leg from the ground and keep the knee straight. During the lifting process, try pointing toes upward slightly. The leg should raise up to at least 25 degrees hip abduction angle. The measurement is primarily the hip abduction angle, that is, the angle formed between the ground and the abducting leg. The secondary measurement is the knee angle to check if the knee remains straight during each repetition.

(3) Straight leg raise. The essence of this exercise is to practice lifting the entire leg while lying on the back. More specifically, the patient should first lie on the back with knee straight for the practicing leg. The patient may bend opposite knee for support. The patient should tighten quadriceps muscle on front of thigh of the practicing leg. Then, raise the leg off ground while keeping the thigh muscle tight. After that, the patient may return the leg to the start position. The hip must reach 45 degrees flexion and the knee must be full extension during the exercise. The measurement is primarily the hip flexion angle, basically, the angle formed between the ground and the practicing leg. The secondary measurement is the knee angle.

(4) Ankle pump. In this exercise, the patient should begin with foot pulled up to the shin and then perform a pumping action as if one was pushing on the gas pedal. During the exercise, make sure the knee is straight. Also, the ankle must reach neutral dorsiflexion, that is, the angle between the bottom of the foot and the lower leg is 90 degrees. The primary measurement is the ankle dorsiflexion angle. The secondary measurement is the knee angle.

3.2 Feasibility study with Kinect

The system uses the second generation of the Microsoft Kinect (the device that came with Xbox One), typically referred to as Kinect v2. The system is designed with the Kinect v2 software development kit and the Unity 3D game development platform. The former enables us to collect skeleton joint data from the patient to assess the patient's movements. The rule for each exercise is implemented based on the framework that we previously proposed[11], which enables our program to automatically perform repetition count and range of motion measurement, as well as assess the compliance with the exercise requirement. Unity is used to implement a virtual reality interface with an avatar display. The avatar would demonstrate the required movements for each exercise. Once the patient is ready to practice, the avatar would mirror the actual movements captured by Kinect (and later by the inertial sensors as well). Some basic feedback information is also displayed together with the avatar. At presence, it is limited to the repetition count and range of motion. In the future, we plan to add more rule-specific feedback. The entire system is written in C# programming language.

The Kinect v2 is positioned roughly about 5 feet above the ground and tilted downward for approximately 10–15 degrees so that the human subject is fully in the view of the Kinect sensor. The Kinect sensor is connected to a Windows Personal Computer (PC) using a USB cable. The subject is sitting or lying down on the ground approximately 4–5 feet away from the Kinect sensor. The subject is aligned roughly in parallel to the Kinect sensor, that is, instead of facing directly to the Kinect sensor, the subject rotates left by about 90 degrees so that the right leg can be seen clearly by the Kinect sensor, as shown in Fig. 1. All skeleton joint data were processed in real-time and logged to comma-separated-value files that can be analyzed offline. For the feasibility investigation, we intentionally used a stick-figure avatar instead of a 3D avatar to mirror the movements captured so that we can observe and examine the reported joint positions as reported by Kinect. Based on our observation, it is apparent that Kinect is not capable of accurately tracking the foot orientation and movements. Hence, the ankle pump exercise is not tested with Kinect.

3.2.1 Quad set

The key movement frames displayed on the virtual reality user interface for the quad set exercise are shown in Fig. 2. The rules used for assessment for the quad set exercise are defined in List 1 (assuming that the right knee is the one that should be exercised). Two key frames are used to define the exercise. Both key frames are defined in terms of the angle formed between the upper leg and the lower leg. The angle is calculated

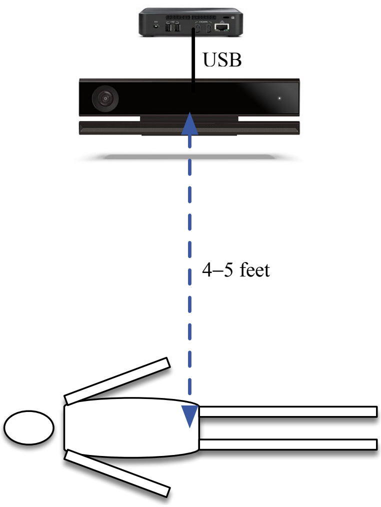

Fig. 1 Experimentation setup.

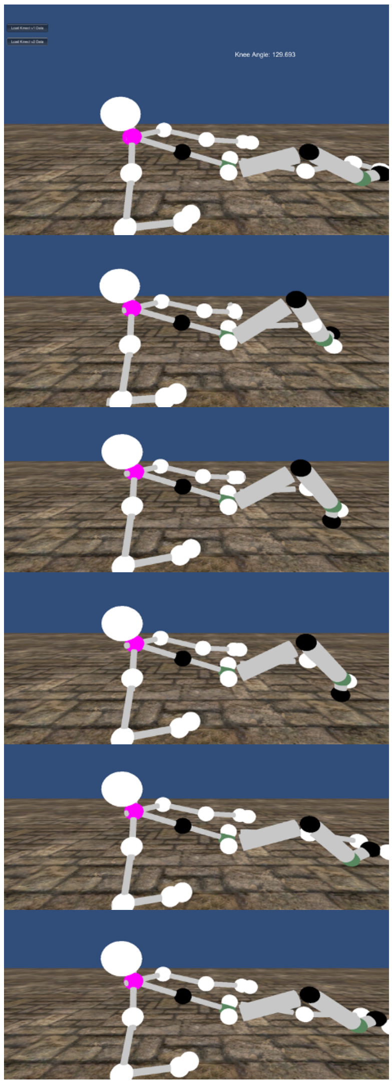

Fig. 2 Key movement frames displayed on the virtual reality user interface for the quad set exercise.

List 1 Rules for the quad set exercise.

```
<ExerciseRules Name="Quad Set">
  <DynamicRule>
    <Configuration>
        <Type>"JointAngle"</Type>
        <CenterJoint>"RightKnee"</CenterJoint>
        <DownstreamJoint>"RightAnkle"</DownstreamJoint>
        <UpstreamJoint>"RightHip"</UpstreamJoint>
        <Angle>"180"</Angle>
        <MaxAngleDeviation> "40" </MaxAngleDeviation>
    </Configuration>
    <Configuration>
        <Type>"JointAngle"</Type>
        <CenterJoint>"RightKnee"</CenterJoint>
        <DownstreamJoint>"RightAnkle"</DownstreamJoint>
        <UpstreamJoint>"RightHip"</UpstreamJoint>
        <Angle>"90"</Angle>
        <MaxAngleDeviation> "10" </MaxAngleDeviation>
    </Configuration>
  </DynamicRule>
</ExerciseRules>
```

based on two vectors. One vector is defined by the knee and hip joints, and the other vector is defined by the knee and the ankle joints. At the initial frame, the ideal knee angle should be 180 degrees. At the end frame, the knee angle should reach at least 90 degrees.

The measured knee angle result for three repetitions is shown in Fig. 3. When the leg is straight, the angle should be close to 180 degrees. The actual measured angle is smaller than that, and there exists some inconsistency across different repetitions. To accommodate the measurement issue, we set a very large tolerance value (of 40 degrees) in the corresponding reference configuration. We could also apply an offset of 20 degrees systematically to alleviate the issue. Indeed, the Kinect measurements sometimes lead to systematic errors for some joints, as previously observed for the sit-to-stand exercise[26]. Fortunately, the knee angle at the initial position is less critical than the reading when the knee is bent, which shows much better accuracy and consistency at around 80 degrees.

3.2.2 Side-lying hip abduction

Figure 4 shows the key movement frames displayed on the virtual reality user interface for the side-lying hip abduction exercise. The rules for the side-lying hip abduction exercise are defined in List 2. Here we re-interpreted the rules defined in natural language so that it is easier to measure based on the collected data. We use the hip angle as formed between the torso and the moving leg instead of that formed between the floor plane and the leg. Hence, the initial pose will have ideally a hip angle of 180 degrees and while the leg is abducting, the hip angle would reduce. This exercise has an invariance rule which states that the knee must be straight, which means the knee angle is 180 degrees.

The measured hip angle and knee angle for 5 repetitions are shown in Fig. 5. As can be seen, the

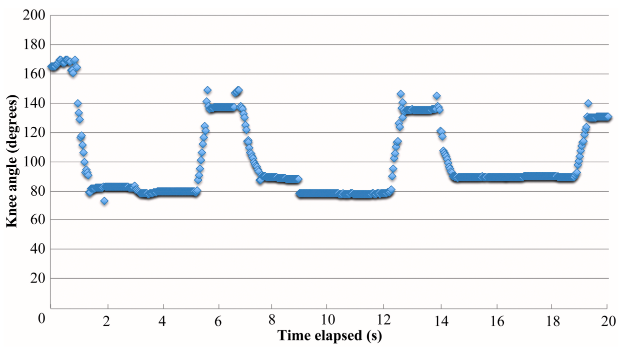

Fig. 3 Measured knee angle during the quad set exercise.

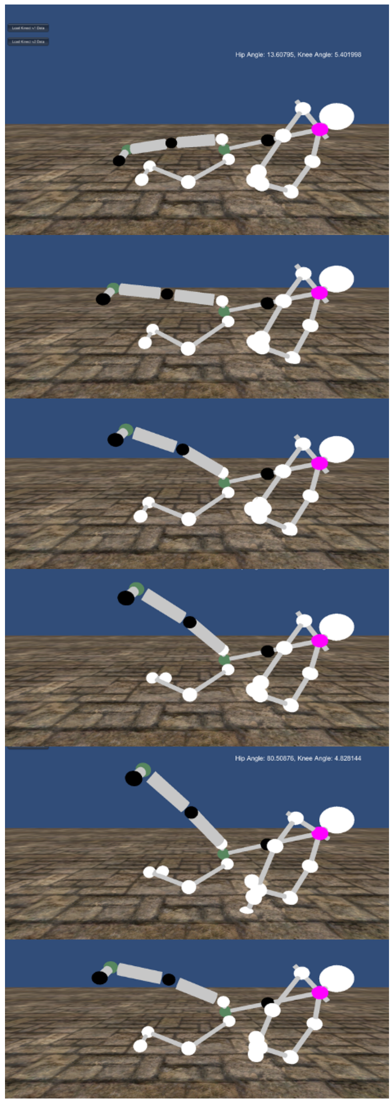

Fig. 4 Key movement frames displayed on the virtual reality user interface for the side-lying hip abduction exercise.

initial hip angle is slightly over 160 degrees instead of 180 degrees. Hence, we set a 20-degree tolerance for this pose. The knee angle fluctuates heavily, but the fluctuations are all within a 20-degree range. Hence, we also use this value as the tolerance value for the invariance rule. Nevertheless, it indicates the challenge of measuring the knee angle during the movements by Kinect.

3.2.3 Straight leg raise

Figure 6 shows the key movement frames displayed on the virtual reality user interface for the straight leg raise exercise. The rules for the straight leg raise exercise are identical to those for the side-lying hip abduction (even though the orientation of the subject is different)

List 2 Rules for the quad set exercise.

```
<ExerciseRules Name="Side-Lying Hip Abduction">
  <DynamicRule>
    <Configuration>
        <Type>"JointAngle"</Type>
        <CenterJoint>"RightHip"</CenterJoint>
        <DownstreamJoint>"RightAnkle"</DownstreamJoint>
        <UpstreamJoint>"RightShoulder"</UpstreamJoint>
        <Angle>"180"</Angle>
        <MaxAngleDeviation> "20" </MaxAngleDeviation>
    </Configuration>
    <Configuration>
        <Type>"JointAngle"</Type>
        <CenterJoint>"RightHip"</CenterJoint>
        <DownstreamJoint>"RightAnkle"</DownstreamJoint>
        <UpstreamJoint>"RightShoulder"</UpstreamJoint>
        <Angle>"90"</Angle>
        <MaxAngleDeviation> "10" </MaxAngleDeviation>
    </Configuration>
  </DynamicRule>
  <InvarianceRule>
    <Configuration>
        <Type>"JointAngle"</Type>
        <CenterJoint>"RightKnee"</CenterJoint>
        <DownstreamJoint>"HipCenter"</DownstreamJoint>
        <UpstreamJoint>"RightAnkle"</UpstreamJoint>
        <Angle>"180"</Angle>
        <MaxAngleDeviation>"20"</MaxAngleDeviation>
    </Configuration>
  </InvarianceRule>
</ExerciseRules>
```

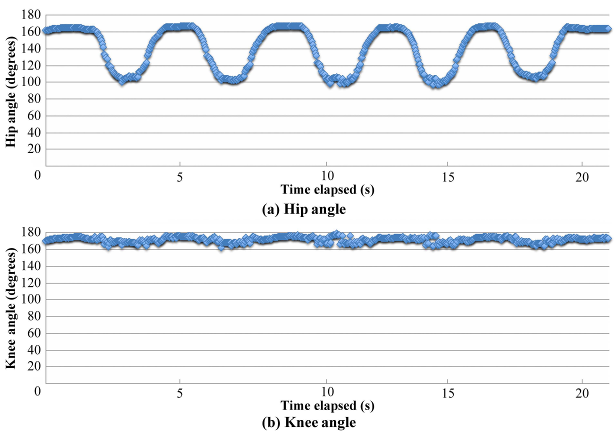

Fig. 5 Hip angle and the knee angle measurement for the side-lying hip abduction exercise.

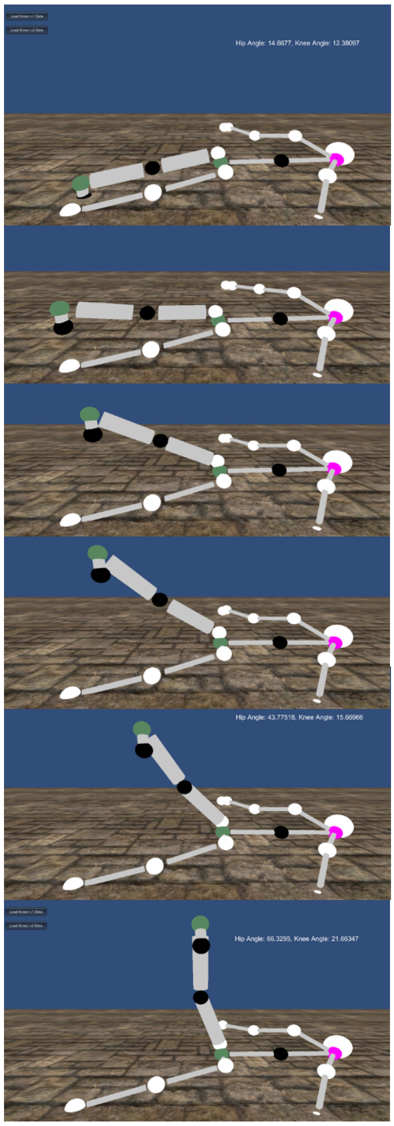

Fig. 6 Key movement frames displayed on the virtual reality user interface for the straight leg raise exercise.

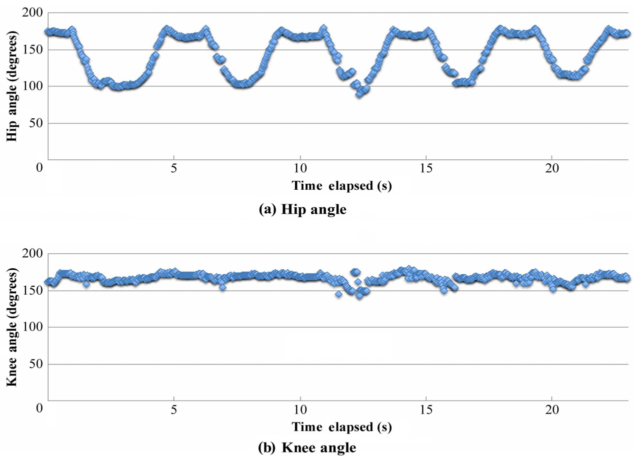

Fig. 7 Hip angle and the knee angle measurement for straight leg raise exercise.

as shown in List 2. The results are rather similar to those of the side-lying hip abduction. However, as shown in Fig. 7, the measured knee angle are visibly more unstable, with sometimes jittering beyond 20 degrees. This revealed that it is challenging for Kinect to accurately track the knee movements in our setup. In future work, we will explore alternative ways of positioning the Kinect sensor for better results.

As can be seen in the screenshots displayed in Fig. 6, the foot position tracking is not reliable. Hence, we decided to use an internal sensor to collect data and track the movements for the ankle pump exercise.

3.3 Integrating with inertial sensing

We experimented with two commercial off-the-shelf inertial sensors Inertial Measurement Unit (IMU), one is from Opal[27], and the other is from Shimmer[28]. The

Opal sensor is much more expensive than the Shimmer sensor. The measurements with the Opal sensor did seem to be more reliable. However, the sensor requires constant re-calibration, which significantly hampers its usability for patients performing rehabilitation exercises at home. The Shimmer sensor is essentially plug-and-play and for the type of measurements we need, no recalibration is necessary. Hence, we decided to use the Shimmer sensor in this study.

To integrate IMU sensing data non-intrusively, we used a Transmission Control Protocol (TCP) connection between the Unity/Kinect program and the Shimmer capture program (open source, written in Java, which we modified by adding a TCP connection to pass the data collected to the Unity/Kinect program) running on the same Windows PC. The Shimmer sensor is connected to the PC using Bluetooth. The system setup is illustrated in Fig. 8. The Shimmer coordinate system is also shown in Fig. 8. The sensor is placed on the top surface of the foot for the ankle pump exercise and it is orientated in such a way that z-axis is point upward (if the foot is standing on the floor), and x-axis is pointing from the front of the foot to the heel side. With this orientation, the movements in the ankle pump exercise fall within x-z plane. As such, we could use the accelerometer sensor's x and z components to calculate the tilt angle to estimate the ankle angle. While it works generally well, there exist occasional jitters. To improve the measurement accuracy and smoothness, we decided to fuse the accelerometer and gyroscope measurements using a simple complementary filter[29], as given by $\theta = (0.98) \times (\theta + \text{gyro} \times \text{dt}) + (0.02) \times \theta_{\text{acc}}$, where $\theta_{\text{acc}} = \arctan(\text{acc}_x/\text{acc}_z)$, θ is the final ankle angle we use, gyro is the gyroscope reading (i.e., the speed of rotation), and dt is the sampling period (i.e., the time elapsed between two consecutive readings).

The measured ankle angle for 6 repetitions is shown in Fig. 9. For convenience, we redefined the ankle angle to be relative to when the foot top surface is horizontal (i.e., perpendicular to the lower leg) and use this pose as the initial pose for the exercise. The foot will first flex up towards the leg and then pump down.

4 Discussion

As we have reported earlier, the measurement of some angles has exhibited relatively large deviation from the expected value. For example, the knee angles measured in the quad exercise showed roughly a 40-degree deviation. Based on our past experiences[26], this error is probably caused by the wrong estimation of the hip joint. As can be seen in Fig. 2, the hip is almost side-way

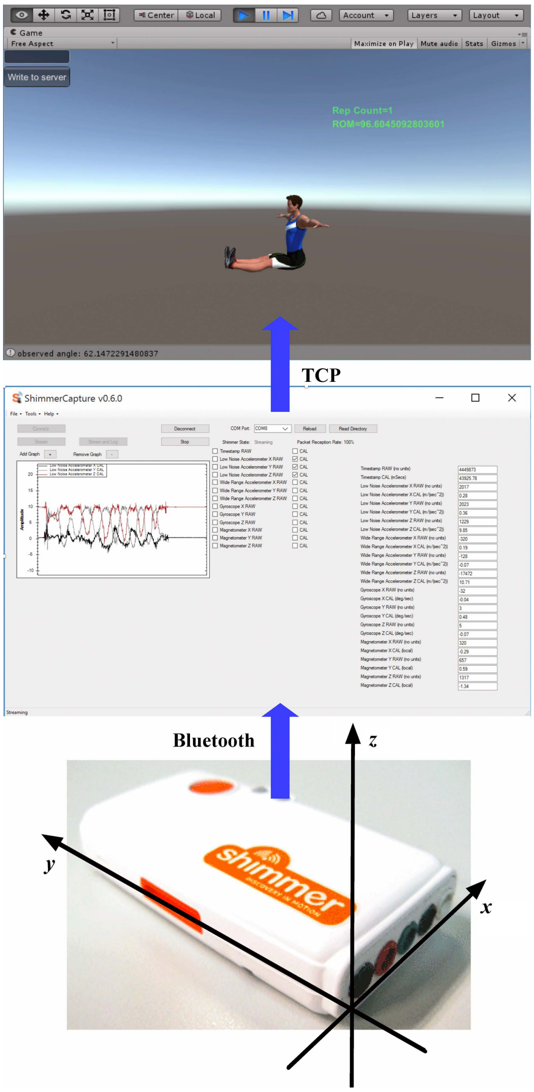

Fig. 8 System setup that integrates IMU sensing.

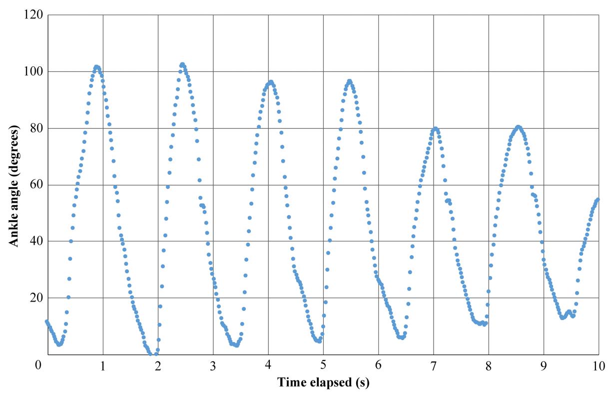

Fig. 9 Measured ankle angle for 6 repetitions for the ankle pump exercise.

to the Kinect, which could make it very challenging for the Kinect to recognize. Even when facing directly to Kinect, we have found that the hip measurement has systematic errors[26].

Unfortunately, in most cases, only qualitative categorical feedback for patient is needed, such as excellent, very good, and good[30]. This significantly reduces the requirements on measurement accuracy and hence allows us to use a fairly generous tolerance in the rules for assessing the quality and correctness of the rehabilitation exercises. We have explored the integration of fuzzy logic into the motion tracking system for providing categorical feedback to patients in several rehabilitation exercises[30].

Limitation. Due to the lack of resources, we did not compare the measurement results with those of a gold-standard human activity tracking system (such as a multi-camera system) to establish the accuracy of the proposed system. Furthermore, we did not conduct any human-subject tests to assess the usability of the system as well as the accuracy of the system for patients with various body types. Such missing steps could be conducted only after substantial research funding is acquired in the future.

5 Conclusion

In this paper, we presented the design and implementation of an interactive avatar-based system that facilitates TKR patients performing rehabilitation exercises at the comfort of home. We focused on four specific exercises commonly used for TKR patient rehabilitation. We found that while the hip angle and the knee angle can be reliably tracked by Kinect v2, the ankle movements are not. Hence, we augmented the system with a Shimmer IMU sensor, which is placed on the patient's foot surface. We show that the integrated system can be used to track movements and to perform real-time assessment on the quality and quantity of the movements using the rules defined in the form of XML for TKR rehabilitation. The virtual reality interface currently has limited feedback information, including the repetition count and the range of motion of the key joint. In the future, we plan to enrich the interface with additional feedback such as whether or not a specific rule is violated during the exercise.

References

[1] I. M. Tomek, D. C. Goodman, A. R. Esty, J. E. Bell, and E. S. Fisher, Trends and regional variation in hip, knee and shoulder replacement, https://folio.iupui.edu/bitstream/handle/10244/1014/Joint_Replacement_0410.pdf?sequence=1, 2010.

[2] P. Cram, X. Lu, S. L. Kates, J. A. Singh, Y. Li, and B. R. Wolf, Total knee arthroplasty volume, utilization, and outcomes among medicare beneficiaries, 1991–2010, *JAMA*, vol. 308, no. 12, pp. 1227–1236, 2012.

[3] J. A. Kleim and T. A. Jones, Principles of experience-dependent neural plasticity: Implications for rehabilitation after brain damage, *J. Speech Lang. Hear. Res.*, vol. 51, no. 1, pp. S225–S239, 2008.

[4] D. Tino and C. Hillis, The full can exercise as the recommended exercise for strengthening the supraspinatus while minimizing impingement, *Strength Cond. J.*, vol. 32, no. 5, pp. 33–35, 2010.

[5] R. Lun and W. B. Zhao, A survey of applications and human motion recognition with microsoft kinect, *Int. J. Pattern Recognit. Artif. Intell.*, vol. 29, no. 5, p. 1555008, 2015.

[6] W. B. Zhao, A concise tutorial on human motion tracking and recognition with microsoft kinect, *Sci. China Inf. Sci.*, vol. 59, no. 9, p. 93101, 2016.

[7] E. Knippenberg, J. Verbrugghe, I. Lamers, S. Palmaers, A. Timmermans, and A. Spooren, Markerless motion capture systems as training device in neurological rehabilitation: A systematic review of their use, application, target population and efficacy, *J. Neuroeng. Rehabil.*, vol. 14, no. 1, p. 61, 2017.

[8] A. Da Gama, P. Fallavollita, V. Teichrieb, and N. Navab, Motor rehabilitation using kinect: A systematic review, *Games Health J.*, vol. 4, no. 2, pp. 123–135, 2015.

[9] W. B. Zhao, D. D. Espy, M. A. Reinthal, and H. Feng, A feasibility study of using a single kinect sensor for rehabilitation exercises monitoring: A rule based approach, in *Proc. 2014 IEEE Symp. on Computational Intelligence in Healthcare and e-Health*, Orlando, FL, USA, 2014, pp. 1–8.

[10] W. B. Zhao, H. Feng, R. Lun, D. D. Espy, and M. A. Reinthal, A kinect-based rehabilitation exercise monitoring and guidance system, in *Proc. 2014 IEEE 5th Int. Conf. on Software Engineering and Service Science*, Beijing, China, 2014, pp. 762–765.

[11] W. B. Zhao, M. A. Reinthal, D. D. Espy, and X. Luo, Rule-based human motion tracking for rehabilitation exercises: Realtime assessment, feedback, and guidance, *IEEE Access*, vol. 5, pp. 21 382–21 394, 2017.

[12] W. B. Zhao, R. Lun, D. D. Espy, and M. A. Reinthal, Rule based realtime motion assessment for rehabilitation exercises, in *Proc.* 2014 *IEEE Symp. on Computational Intelligence in Healthcare and e-health*, Orlando, FL, USA, 2014, pp. 133–140.

[13] W. B. Zhao, D. D. Deborah, M. A. Reinthal, B. Ekelman, G. Goodman, and J. Niederriter, Privacy-aware human motion tracking with realtime haptic feedback, in *Proc.* 2015 *IEEE Int. Conf. on Mobile Services*, New York, NY, USA, 2015, pp. 446–453.

[14] W. B. Zhao, R. Lun, C. Gordon, A. B. M. Fofana, D. D. Espy, M. A. Reinthal, B. Ekelman, G. D. Goodman, J. E. Niederriter, and X. Luo, A human-centered activity tracking

system: Toward a healthier workplace, *IEEE Trans. Human-Mach. Syst.*, vol. 47, no. 3, pp. 343–355, 2017.

[15] W. B. Zhao, Q. Wu, A. Reinthal, and N. Zhang, Design, implementation, and field testing of a privacy-aware compliance tracking system for bedside care in nursing homes, *Appl. Syst. Innov.*, vol. 1, no. 1, p. 3, 2018.

[16] M. O'Reilly, B. Caulfield, T. Ward, W. Johnston, and C. Doherty, Wearable inertial sensor systems for lower limb exercise detection and evaluation: A systematic review, *Sports Med.*, vol. 48, no. 5, pp. 1221–1246, 2018.

[17] W. Y. Wong, M. S. Wong, and K. H. Lo, Clinical applications of sensors for human posture and movement analysis: A review, *Prosthet. Orthot. Int.*, vol. 31, no. 1, pp. 62–75, 2007.

[18] C. Y. Chiang, K. H. Chen, K. C. Liu, S. J. P. Hsu, and C. T. Chan, Data collection and analysis using wearable sensors for monitoring knee range of motion after total knee arthroplasty, *Sensors*, vol. 17, no. 2, p. 418, 2017.

[19] Y. P. Huang, Y. Y. Liu, W. H. Hsu, L. J. Lai, and M. S. Lee, Monitoring and assessment of rehabilitation progress on range of motion after total knee replacement by sensor-based system, *Sensors*, vol. 20, no. 6, p. 1703, 2020.

[20] M. E. Kayaalp, A. N. Agres, J. Reichmann, M. Bashkuev, G. N. Duda, and R. Becker, Validation of a novel device for the knee monitoring of orthopaedic patients, *Sensors*, vol. 19, no. 23, p. 5193, 2019.

[21] S. R. Small, G. S. Bullock, S. Khalid, K. Barker, M. Trivella, and A. J. Price, Current clinical utilisation of wearable motion sensors for the assessment of outcome following knee arthroplasty: A scoping review, *BMJ Open*, vol. 9, no. 12, p. e033832, 2019.

[22] L. Donath, R. Rössler, and O. Faude, Effects of virtual reality training (exergaming) compared to alternative exercise training and passive control on standing balance and functional mobility in healthy community-dwelling seniors: A meta-analytical review, *Sports Med.*, vol. 46, no. 9, pp. 1293–1309, 2016.

[23] H. S. Lee, Y. J. Park, and S. W. Park, The effects of virtual reality training on function in chronic stroke patients: A systematic review and meta-analysis, *BioMed Res. Int.*, vol. 2019, p. 7595639, 2019.

[24] M. Yates, A. Kelemen, and C. S. Lanyi, Virtual reality gaming in the rehabilitation of the upper extremities post-stroke, *Brain Inj.*, vol. 30, no. 7, pp. 855–863, 2016.

[25] M. J. Chen, Y. Li, X. Luo, W. P. Wang, L. Wang, and W. B. Zhao, A novel human activity recognition scheme for smart health using multilayer extreme learning machine, *IEEE Internet Things J.*, vol. 6, no. 2, pp. 1410–1418, 2019.

[26] W. B. Zhao, D. D. Espy, and M. A. Reinthal, Assessment of sit-to-stand movements using a single kinect sensor: A preliminary study in healthy subjects, *Int. J. Healthc. Inf. Syst. Inf.*, vol. 14, no. 1, pp. 29–43, 2019.

[27] R. Jurdak, K. Klues, B. Kusy, C. Richter, K. Langendoen, and M. Brunig, Opal: A multiradio platform for high throughput wireless sensor networks, *IEEE Embedd. Syst. Lett.*, vol. 3, no. 4, pp. 121–124, 2011.

[28] A. Burns, B. R. Greene, M. J. McGrath, T. J. O'Shea, B. Kuris, S. M. Ayer, F. Stroiescu, and V. Cionca, SHIMMER™—A wireless sensor platform for noninvasive biomedical research, *IEEE Sens. J.*, vol. 10, no. 9, pp. 1527–1534, 2010.

[29] M. Euston, P. Coote, R. Mahony, J. Kim, and T. Hamel, A complementary filter for attitude estimation of a fixed-wing UAV, in *Proc.* 2008 *IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, Nice, France, 2008, pp. 340–345.

[30] W. B. Zhao, R. Lun, D. D. Espy, and M. A. Reinthal, Realtime motion assessment for rehabilitation exercises: Integration of kinematic modeling with fuzzy inference, *J. Artif. Intell. Soft Comput. Res.*, vol. 4, no. 4, pp. 267–285, 2014.

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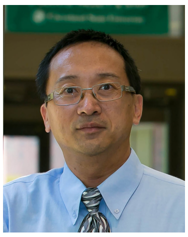

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