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Real-Time Limb Motion Tracking with a Single IMU Sensor for Physical Therapy Exercises

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Abstract— **Limb exercises are common in physical therapy to improve range of motion (RoM), strength, and flexibility of the arm/leg. To improve therapy outcomes and reduce cost, motion tracking systems have been used to monitor the user's movements when performing the exercises and provide guidance. Traditional motion tracking systems are based on either cameras or inertial measurement unit (IMU) sensors. Camera-based systems face problems caused by occlusion and lighting. Traditional IMU-based systems require at least two IMU sensors to track the motion of the entire limb, which is not convenient for use. In this paper, we propose a novel limb motion tracking system that uses a single 9-axis IMU sensor that is worn on the distal end joint of the limb (i.e., wrist for the arm or ankle for the leg). Limb motion tracking using a single IMU sensor is a challenging problem because 1) the noisy IMU data will cause drift problem when estimating position from the acceleration data, 2) the single IMU sensor measures the motion of only one joint but the limb motion consists of motion from multiple joints. To solve these problems, we propose a recurrent neural network (RNN) model to estimate the 3D positions of the distal end joint as well as the other joints of the limb (e.g., elbow or knee) from the noisy IMU data in real time. Our proposed approach achieves high accuracy with a median error of 7.2/7.1 cm for the wrist/elbow joint in leave-one-subject-out cross validation when tracking the arm motion, outperforming the state-of-the-art approach by more than 10%. In addition, the proposed model is lightweight, enabling real-time applications on mobile devices.**

Clinical relevance— **This work has great potential to improve limb exercises monitoring and RoM measurement in home-based physical therapy. It is also cost effective and can be made available widely for immediate application.**

I. INTRODUCTION

The U.S. physical therapy (PT) market is estimated at \$34.5 billion in 2018, with a 6.2% annual growing rate, to \$45.7 billion by 2023 [1]. Traditional PT is hampered by the high cost of clinical training programs and the shortage of physical therapists. Based on current trends in the PT workforce, the shortage of physical therapists could reach over 27,000 by 2025 in the U.S. [2]. Moreover, in-person clinic visits are becoming concerning due to COVID-19. In addition to clinic training programs, home-based programs are also facing challenges including low compliance and poor outcomes. Argent et al. have discussed that nonadherence to home rehabilitation exercises is as high as 50%, which can be potentially improved by connected health solutions [3]. Without the supervision of professional therapists at home, incorrect motion may lead to suboptimal outcomes or even injuries [4].

As a result of these challenges, popularity has grown for home-based virtual PT systems using motion tracking sensors to monitor the patient's motion and provide guidance [5], [6], [7]. Traditional motion tracking systems include 1) camera-based systems, which use RGB/RGB-D cameras and computer vision techniques to estimate user's motion [8], [9]. However, camera-based approaches may raise privacy issues and accuracy may be weakened by occlusion and low image/video quality. 2) Wearable-based systems, which use multiple inertial measurement unit (IMU) sensors to track the motion [10], [11], [12]. In this paper, we focus on tracking the motion of limb exercises, which are widely used in PT to improve the range of motion (RoM), strength, and flexibility of the arm/leg. To track the motion of the limb, traditional IMU-based tracking systems require at least two IMU sensors (one on the upper extremity and the other one on the lower extremity) to track the orientation of the bones [10], [11], [12]. To improve the usability, we propose a novel approach to track the limb motion using a single IMU sensor that is worn on the end joint of the limb (e.g., wrist or ankle). Firstly we present the following challenges in addressing this problem.

Inaccuracy of IMU Sensors in Position Estimation. A common problem of IMU sensors is *drift* when calculating velocity/position from continually integrating acceleration data. Due to integration, a constant error in acceleration results in a linear/quadratic error in velocity/position. To fix the drift problem in pedestrian navigation systems, researchers have developed the zero velocity update (ZUPT) algorithm, which resets the velocity error in each walking cycle [13]. However, the zero velocity interval does not exist in other types of motion. Therefore, positions cannot be calculated directly from acceleration by integration.

Complexity of Limb Motion. Limb motion includes the movement of multiple joints. For simplicity, arm motion is used as an example here, as well as in the following sections. In robotics, the human arm is typically modelled as seven degrees of freedom including: shoulder (abduction-adduction q_1, flexion-extension q_2, internal-external rotation q_3), elbow (flexion-extension q_4), forearm (pronation-supination q_5), and wrist (flexion-extension q_6, radial-ulnar q_7) [12]. However, only one joint can be directly tracked using a single IMU sensor and it is challenging to infer the motion of other joints.

Recently there has been progress on limb motion tracking using a single IMU sensor. ArmTrak [14] uses a smartwatch

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to track the user's arm motion, including an offline version (with higher tracking accuracy but high latency) and a real-time version (with lower tracking accuracy). LimbMotion [15] uses acoustic ranging to detect the distance between the smartwatch and an edge device. Its accuracy outperforms ArmTrak by 32%, but the use of edge device decreases its usability.

In this paper, we propose a novel approach using deep learning and anatomical considerations to improve the tracking accuracy using one IMU sensor and without any edge device. We propose the following insights to address the drift problem caused by calculating position from integrating acceleration. Firstly, human joints have limited RoM [16] and fixed bone length. Thus, the possible positions of the elbow and the wrist are limited. Secondly, the orientation of the IMU sensor is correlated with the joint positions. Therefore, orientation data can help further reduce the uncertainty in joint position estimation. Based on the above insights, we propose to use the combination of acceleration and orientation data of the IMU sensor to estimate the elbow and wrist positions in real time. We use a recurrent neural network (RNN) model to utilize the temporal information, which is essential in estimating the current position of the joints. Our proposed system outperforms the traditional motion tracking systems in the following aspects.

Improved Usability and Privacy Preserving. The proposed system can be implemented on any wrist/ankle mounted device that has a IMU sensor. This significantly improves the usability and potential for pervasiveness compared with traditional IMU-based systems that require at least two IMU sensors. Compared with camera-based systems, the proposed system preserves user privacy by using an IMU sensor instead of capturing the user images/videos. Compared with LimbMotion [15], our approach can track the arm motion accurately without an extra edge device except the single IMU sensor.

High Tracking Accuracy. Our approach achieves the median error of $7.2/7.1cm$ for the wrist/elbow joints, which outperforms ArmTrak [14] and LimbMotion [15] by more than 10%.

Real-Time Tracking with Low latency. In the offline version of ArmTrak [14], a Hidden Markov Model (HMM) is used to find out the optimal state sequence. However, HMM is computationally expensive and works after the entire input sequence is obtained, which makes the tracking not real time and can only be applied offline. In contrast, our RNN-based model uses only historical data to estimate the current joint positions in real time. Moreover, the proposed RNN-based model is also lightweight with only 5550 parameters, which enables mobile applications with low latency.

II. METHODOLOGY

Firstly, we define three coordinate systems as follows (see Fig. 1). **User coordinate system** S_{user}: origin at the shoulder, $x-$, $y-$ and $z-$axis points to the left, up, and forward direction. The final joints tracking results will be represented in S_{user}. **Local earth coordinate system** S_{earth}: the $x-$, $y-$ and $z-$axis points to the east, north, and up. **Sensor coordinate system** S_{sensor}: defined in the sensor. We use the Xsens DOT 9-axis IMU sensor [17] in our experiments.

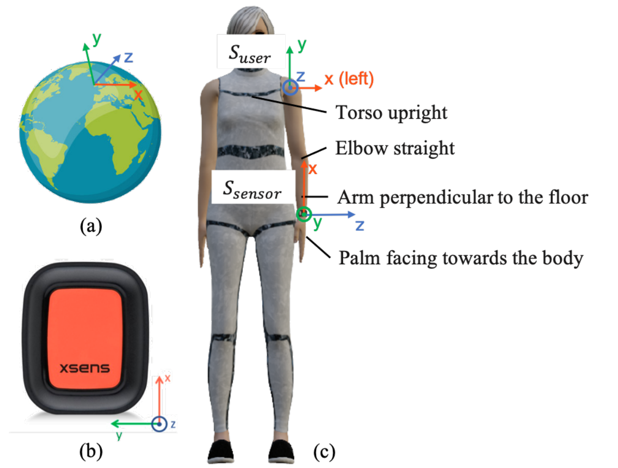

Fig. 1. (a) Local earth coordinate system S_{earth}. (b) Sensor coordinate system S_{sensor}. (c) User coordinate system S_{user} and calibration posture.

Secondly, we assume that the user does not move the torso/shoulder (also used by ArmTrak [14] and LimbMotion [15]), otherwise it becomes an unsolvable problem. For example, if the wrist-mounted IMU sensor detects that the wrist is moving forward, there are two possible situations: 1) the entire user body is moving forward but the arm does not move relative to the torso, or 2) the user is moving only the wrist forward while keeping the torso static. Therefore, the user is required not to move the shoulder/torso during the tracking, which we consider feasible for most limb exercises in physical therapy.

The system diagram is shown in Fig. 2. The built-in sensor fusion module of the Xsens DOT IMU sensor processes the raw data from the accelerometer, gyroscope and magnetometer, and outputs the 3D orientation and free acceleration data (i.e., the acceleration from which the local gravity is deducted), with a $60Hz$ output rate. The 3D orientation data provided by the Xsens DOT sensor represent the orientation of S_{sensor} with respect to S_{earth}. The free acceleration data are in S_{earth}. Since the final joints tracking results will be presented in S_{user}, the transformation between the three coordinate systems are needed. We apply a user orientation identification module to identify the user's orientation when using the system and convert the IMU data to the user coordinate system S_{user}. Then we propose an RNN-based joints tracking model that takes the free acceleration and 3D orientation data as input and estimates the positions of the wrist and the elbow in real time. In this paper, we focus on the major five degrees of freedom $q_1 \sim q_5$. The wrist rotations q_6 and q_7 are beyond the scope of this paper. For the major five degrees of freedom, $q_1 \sim q_4$ can be characterized by the positions of the wrist and the elbow joint. The forearm pronation-supination q_5 can be represented by the orientation of the IMU sensor that is worn on the wrist.

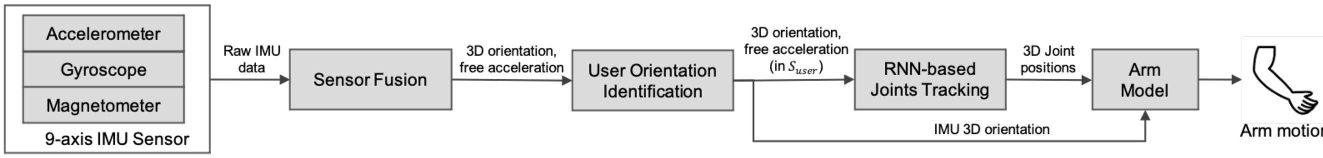

Fig. 2. Diagram of the proposed arm tracking system.

A. User Orientation Identification

Before real-time tracking, the user needs to perform a simple calibration posture (see Fig. 1(c)) for about 3 seconds for orientation identification. Based on the calibration posture, the transformation between S_{sensor} and S_{user} is

$$R_{sensorToUser} = \begin{bmatrix} 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}. \tag{1}$$

As mentioned above, the 3D orientation output of Xsens DOT is the orientation of S_{sensor} with respect to S_{earth}. Therefore, we calculate the average 3D orientation when the user is performing the calibration posture as the rotation between S_{sensor} and S_{earth}, i.e., $S_{earthToSensor}$. Then the rotation between S_{user} and S_{earth} can be calculated as

$$R_{earthToUser} = R_{sensorToUser} \times R_{earthToSensor}. \tag{2}$$

It represents the user's orientation with respect to S_{earth}, i.e., which direction the user is facing. As it is assumed that the user will not move the torso/shoulder, $R_{earthToUser}$ is fixed during the tracking and is used to convert the 3D orientation and free acceleration data from the IMU sensor to S_{user}.

B. RNN-based Joints Tracking Model

We selected RNN instead of other neural networks as it can process and preserve the temporal information in sequential data. Compared to other machine learning and statistic learning algorithms that can also process time series, RNN is more efficient at making real-time estimations/predictions. The network architecture is shown in Fig. 3. At each time frame t, input of the network x_t includes the free acceleration and 3D orientation (quaternions) data, which have been transformed into S_{user}. x_t is sent to a Gated Recurrent Unit (GRU) layer (36 units) followed by a Fully Connected (FC) layer (6 units) FC2. The real-time output y_t includes the positions of the elbow and the wrist at current frame t. For the GRU layer, it passes the previous hidden state S_{t-1} to the current frame t so that the network can learn and preserve the temporal information. In addition to the real-time IMU data, the initial joint positions and velocities are also crucial when calculating the current joint positions. Therefore, we propose to incorporate the initial positions and velocities into the RNN model as follows: an FC layer (FC1) is trained to convert the initial joint positions and velocities to the initial state of the GRU layer. Unlike traditional GRU models that use the default zero-filled initial state, our model learns the initial state from the initial joint positions and velocities, thereby accurately estimating the real-time joint positions. The RNN-based model is also lightweight with

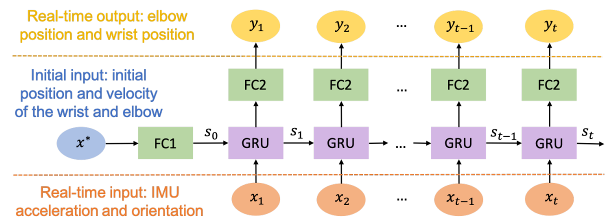

Fig. 3. Architecture of the RNN-based joints tracking model.

only 5550 parameters, which is much smaller than many common neural networks [18].

C. Training and Application

Skeleton normalization for ground truth measurement. To train the RNN-based joints tracking model, the ground-truth joint positions can be either measured by RGB/RGB-D cameras or multiple IMU sensors. For RGB/RGB-D cameras, the output joint positions typically represent the true distance in the camera space and subjects of different body sizes will have different joint positions even with the same posture. Using normalized training data is important for training the model. Therefore, we propose to normalize the ground-truth joint positions and transform them into S_{user}. For IMU-based tracking systems, the normalized skeleton is also required. When applying the model, the output joint positions are also based on the pre-defined normalized skeleton and can be rescaled based on the true size of the user body.

Data collection. Typically, training an RNN model involves collecting N sequences with the same length r (here we use a recording to indicate collecting a sequence from a subject). However, because the user orientation identification module is needed in this application, each subject would need to repeat the user orientation identification step for each recording, making data collection very time and labor consuming. To address this problem, we propose a novel data collection approach that requires only five recordings from each subject. Each subject will change the body orientation and perform user orientation identification for each recording. However, instead of recording a sequence of length r, we collect a much longer sequence of length L ($L \approx 50r$) for each recording. Then we segment the long sequence into multiple segments of length r, with a 50% overlap with each other. In this way, we can get $L/(50\%r) \approx 100$ sequences from each long recording, which is much more convenient and effective than collecting 100 recordings from the subject separately. Although the segmented sequences have different initial joint positions and velocities, we use the FC1 layer to convert them to the initial state of the GRU layer.

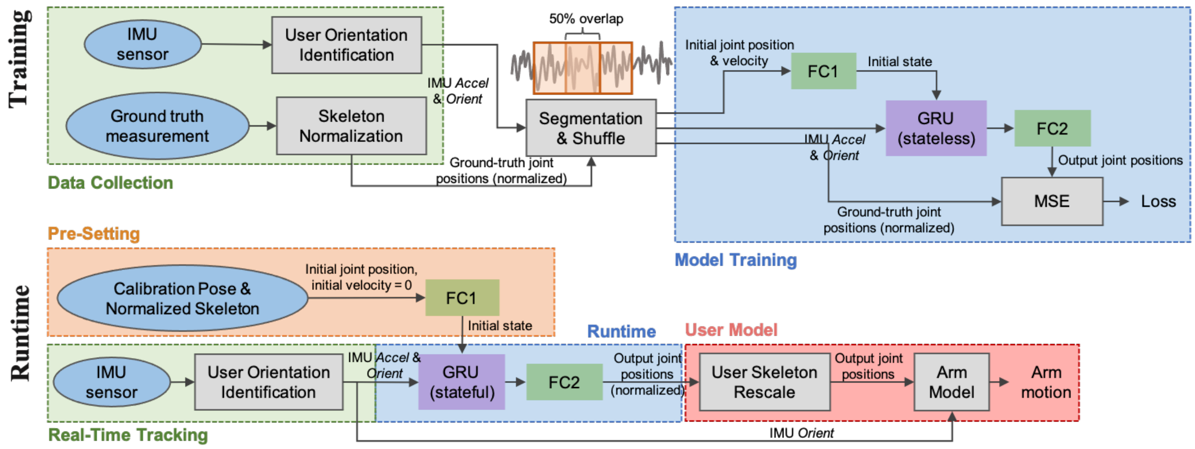

Fig. 4. Data collection, model training and runtime.

Model training. The first half of Fig. 4 shows the details of our data collection and model training process. The acceleration and orientation data are captured by the IMU sensor and transformed into S_{user} based on the user orientation identification results. The ground-truth joint positions are normalized by a pre-defined skeleton. The IMU data and ground truth are segmented into shorter sequences and shuffled for training. When training the model, the GRU layer is set as stateless and its initial state is learned from the initial joint positions and velocities. The FC2 layer outputs the estimated joint positions. The loss is calculated as the mean square error (MSE) between the output joint positions and the ground-truth joint positions.

Runtime. During runtime (shown in the bottom half of Fig. 4), the user still needs to perform user orientation identification before the real-time tracking. Unlike training process, the initial joint velocities are zero as the user keeps static during the calibration posture. The initial positions of the elbow and the wrist are

$$p_0^{elbow} = (0, -l_u, 0), \tag{3}$$

$$p_0^{wrist} = (0, -(l_u + l_f, 0), \tag{4}$$

where l_u and l_f are the length of the upper arm and the forearm defined in the normalized skeleton. The initial joint positions and velocities are sent to the FC1 layer and its output is used to set the initial state of the GRU layer. The initial state of the GRU layer can be set before runtime (once the model is optimized during training) as it does not rely on any real-time input from the IMU sensor. During real-time tracking, the acceleration and orientation data are captured by the IMU sensor and transformed into S_{user}. The GRU layer is set as stateful so that its state can be passed to the next time frame. The FC2 layer outputs the real-time joint positions, which is based on the normalized skeleton. Then we can rescale the joint positions according to the size of the user skeleton.

III. RESULTS AND DISCUSSIONS

To validate the proposed system, we collected data from 8 subjects (6 males, 2 females). Each subject was wearing two IMU sensors on the arm (one on the wrist and the other one on the upper arm) and performing some arm motion in front of the Kinect v2 RGB-D camera. The IMU sensor worn on the upper arm was only used to calculate the ground truth. Each subject performed four sessions of free-form arm motion and a drawing/writing session. We collected 247084-frame IMU data (frame rate $60Hz$) and 122609-frame Kinect data (frame rate $30Hz$) in total, amounting to about 4000 seconds. The Kinect data have been synchronized with the IMU data.

The ground-truth joint positions have been calculated in two different ways: 1) **2IMU**. The 3D orientation data from the two IMU sensors were used to calculate the rotations of the upper arm and forearm from the initial calibration posture as the ground truth. 2) **Kinect**. We also used the joints tracking results from Kinect v2 as the ground truth. The proposed RNN-based joints tracking model was trained and validated using the above two ways of ground truth measurement separately. Both ground truth measurements were normalized. As the tracking error might be correlated with the arm length, we used the average arm length $47.25cm$ in LimbMotion [15] for fair comparison. The upper arm to forearm ratio was based on the anthropometric average male data (forearm length = $27cm$, upper arm length = $34cm$) [19]. For both methods, the input to the RNN model includes only the data from the IMU sensor worn on the wrist.

The proposed RNN-based joints tracking model is trained using the Adam optimizer [20] with a learning rate of 0.001, and tested using both leave-one-session-out and leave-one-subject-out cross validation. We have tested the efficiency of the model on an Intel Core i7-8565U CPU. The average running time is about $3.8ms$ per frame, which validates our conclusion that the model is computationally efficient. In terms of accuracy, the tracking error is calculated as the distance between the ground-truth position and the estimated

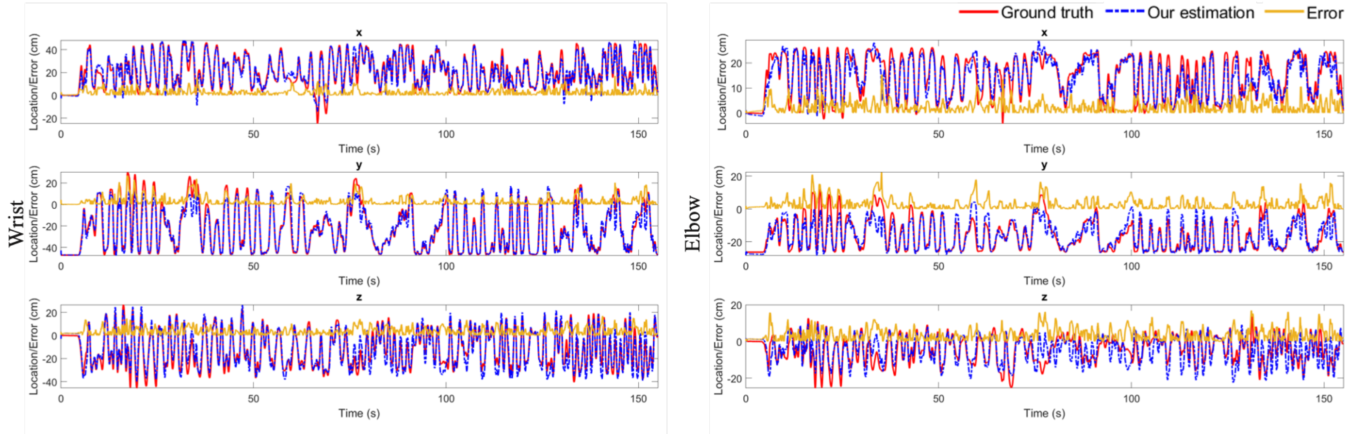

Fig. 5. Tracking results in a complete session.

TABLE I

JOINTS TRACKING RESULTS OF DIFFERENT METHODS.

Method			**Median Error (cm)**		**MAE (cm)**	
			Wrist	Elbow	Wrist	Elbow
ArmTrak [14]		Offline version	9.2	7.9	-	-
		Real-time version	13.3	12.0	-	-
LimbMotion (requiring an edge device) [15]			8.9	8.2	-	-
Our approach	Leave-one-session-out	Kinect as ground truth	11.4	8.1	13.7	10.2
		2IMU as ground truth	6.3	6.0	7.8	7.5
	Leave-one-subject-out	Kinect as ground truth	12.7	9.5	15.0	11.5
		2IMU as ground truth	**7.2**	**7.1**	**8.5**	**8.5**

position of the wrist and the elbow in each frame. Fig. 5 shows the tracking results of a complete session (about 150 seconds) in leave-one-subject-out cross validation. For all three dimensions, the error does not accumulate over time as we use the RNN model to learn the current joint positions from the orientation and acceleration data (both historical and current) instead of calculating position from integration of acceleration.

For overall accuracy evaluation, both ArmTrak [14] and LimbMotion [15] use the median error, which represents the upper limit of error for 50% of the samples. For a more comprehensive representation of the error distribution, we propose to use both median error and Mean Absolute Error (MAE) as the quantitative metrics. The results are shown in Table I. Firstly, the median error of using Kinect as the ground truth in our approach is higher than that of using 2IMU. This is because the average error of Kinect when tracking the wrist and elbow is about $5 \sim 12cm$ (MAE) [8] due to problems such as occlusion, lighting, etc. In our data collection, we also observed that Kinect had much lower accuracy when the arm was moving relatively fast. Therefore, the accuracy of Kinect itself limits the accuracy of our approach when using it as the ground truth. We consider using 2IMU as the ground truth would provide more accurate evaluation as the IMU sensors have higher sampling rate and are free of occlusion and lighting problems.

Secondly, the leave-one-session-out accuracy of our approach is higher than that of leave-one-subject-out, which might be caused by overfitting as the subjects may have performed similar motion in different sessions. Therefore, we consider the leave-one-subject-out cross validation results more representative for real-world applications where the new user's data have never been used in the training set. Comparing the median error of different methods, our results in leave-one-subject-out cross validation achieves the highest accuracy ($7.2/7.1cm$ for the wrist/elbow) when using 2IMU as the ground truth, which outperforms ArmTrak [14] and LimbMotion [15] by more than 10%. Moreover, our approach does not need any extra edge device except the single IMU sensor, thereby significantly improving the usability and potential for pervasiveness compared with the state-of-the-art approach LimbMotion [15].

In addition to the quantitative results, Fig. 6 shows some shapes/digits/letters that the subjects drew/wrote in the drawing session. Although the estimated trajectories contain some noise, they are quite close to the ground-truth trajectories.

The above results have shown that our approach can achieve high accuracy when tracking the arm motion. The same approach can be applied to leg motion tracking, when the user wears an IMU sensor on the ankle. The limb motion tracking system can be used in many applications, e.g., tracking and visualizing the arm/leg motion to provide real-time feedback for physical therapy training. It can also be used for on-demand joint RoM measurement for home use.

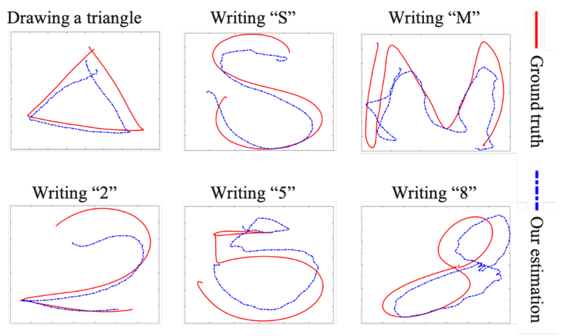

Fig. 6. Visualization results in the drawing/writing session.

For example, people with anterior cruciate ligament (ACL) injury may experience loss of RoM and can use the proposed system to track the progress when regaining the joint RoM. It can also be used by healthy people as a before-injury baseline as people are increasingly using the smartwatch in daily life. Moreover, it can be used in Human-Computer Interaction (HCI) applications by tracking the arm gestures.

IV. CONCLUSIONS

In this paper, we propose an approach to track the real-time motion of the full limb using a single 9-axis IMU sensor. To address the challenges caused by the noisy IMU data and complicated limb motion, we propose an RNN model that utilizes the temporal information to estimate the current position of the joints. Unlike traditional RNN models that use the default zero-filled initial state, our approach learns the initial state from the initial joint positions and velocities, thereby achieving high accuracy in joint position estimation. The proposed model outperforms the state-of-the-art by more than 10%. This work has great potential to improve limb exercises monitoring and RoM measurement in home-based physical therapy. It is also cost effective and can be made available widely for immediate application.

For future work, we will collect data from more subjects and further improve the accuracy of the model. In particular, the drawing/writing results in Fig. 6 show that the output of the RNN model is noisy. We plan to improve the RNN model or apply post-processing for smoother tracking results. Moreover, we plan to implement the proposed approach on mobile devices. Finally, the current system is built upon the assumption that the user does not move the torso during the tracking. In real-world situations, the tracking accuracy may be affected by the user's torso motion. Therefore, we plan to enhance the system to detect the user's torso motion. If any torso motion is detected, the system can provide warning to the user and reset the tracking in a timely manner. We will also explore if torso motion tracking by extra devices can potentially eliminate the effects of torso motion on limb motion tracking to enable wider applications.

REFERENCES

[1] 2020 Outlook: Physical Therapy Clinics & Centers, https://healthcareappraisers.com/2020-outlook-physical-therapy-clinics-centers/, Accessed: Feb. 1 2021.

[2] Congress is Taking Action to Grow the Physical Therapy Workforce, https://www.aptqi.com/congress-is-taking-action-to-grow-the-physical-therapy-workforce/, Accessed: Feb. 1 2021.

[3] R. Argent, A. Daly, and B. Caulfield, "Patient involvement with home-based exercise programs: can connected health interventions influence adherence?" *JMIR mHealth and uHealth* 6.3 (2018): e47.

[4] L. A. King, et al., "Effects of Group, Individual, and Home Exercise in Persons With Parkinson Disease: A Randomized Clinical Trial," *Journal of Neurologic Physical Therapy* 39.4 (2015): 204-212.

[5] B. Galna, et al., "Retraining function in people with Parkinson's disease using the Microsoft kinect: game design and pilot testing," *Journal of neuroengineering and rehabilitation"* 11.1 (2014): 60.

[6] W. Wei, M. Carter, and D. Sujit, "Towards on-demand virtual physical therapist: Machine learning-based patient action understanding, assessment and task recommendation," *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 27.9 (2019): 1824-1835.

[7] T. Y. Lin, C. H. Hsieh, and J. D. Lee, "A kinect-based system for physical rehabilitation: Utilizing tai chi exercises to improve movement disorders in patients with balance ability," *2013 7th Asia Modelling Symposium*. IEEE, 2013.

[8] Q. Wang, et al. "Evaluation of pose tracking accuracy in the first and second generations of microsoft kinect," *2015 international conference on healthcare informatics*. IEEE, 2015.

[9] Mehta, Dushyant, et al. "Vnect: Real-time 3d human pose estimation with a single rgb camera," *ACM Transactions on Graphics (TOG)* 36.4 (2017): 1-14.

[10] C. Caramia, et al. "IMU-based classification of Parkinson's disease from gait: A sensitivity analysis on sensor location and feature selection," *IEEE journal of biomedical and health informatics* 22.6 (2018): 1765-1774.

[11] Hinge Health, https://www.hingehealth.com/, Accessed: Feb. 1 2021.

[12] A. Bertomeu-Motos, et al. "Estimation of human arm joints using two wireless sensors in robotic rehabilitation tasks," *Sensors* 15.12 (2015): 30571-30583.

[13] S. Park, and S. Young, "A zero velocity detection algorithm using inertial sensors for pedestrian navigation systems," *Sensors* 10.10 (2010): 9163-9178.

[14] S. Sheng, H. Wang, and R. Choudhury, "I am a smartwatch and i can track my user's arm," *Proceedings of the 14th annual international conference on Mobile systems, applications, and services.* 2016.

[15] H. Zhou, et al. "LimbMotion: Decimeter-level Limb Tracking for Wearable-based Human-Computer Interaction," *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 3.4 (2019): 1-24.

[16] D. C. Boone, and S. P. Azen, "Normal range of motion of joints in male subjects," *JBJS* 61.5 (1979): 756-759.

[17] Xsens DOT, https://www.xsens.com/xsens-dot, Accessed: Feb. 1 2021.

[18] Common architectures in convolutional neural networks, https://www.jeremyjordan.me/convnet-architectures/, Accessed: Feb. 1 2021.

[19] C. C. Gordon, et al. *Anthropometric Survey of US Personnel: Summary Statistics Interim Report.* Technical Report. No. NATICK/TR-89/027. Natick, MA: US Army Natick Research Development and Engineering Center, 1989.

[20] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," arXiv preprint arXiv:1412.6980 (2014).