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Real-time Virtual Coach using LSTM for Assisting Physical Therapists with End-effector-based Robot-assisted Gait Training

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Abstract— **With the development of robotic technology, the demand for state-of-the-art technology in the field of rehabilitation is rapidly increasing for the elderly and people with disabilities. In this paper, we propose a real-time virtual coach to assist physical therapists with the end-effector-based robot-assisted gait training for stroke survivors using Long Short-Term Memory (LSTM) networks. Our proposed virtual coach consists of the sensor module for data gathering and dataset generation, real-time classification of the pathologic patient gait during the training using LSTM networks, and delivery of the coaching recommendations in an audiovisual form. Our preliminary study determined the selection of coaching recommendations. LSTM networks are trained to provide the selected coaching recommendations. The performance of the proposed virtual coach is verified using classification simulation of an able-bodied person on the rehabilitation robot, G-EO System. The usability was verified through a satisfaction survey of five professional physical therapists.**

I. Introduction

Gait training is one of the most significant rehabilitation trainings to improve the quality of life for stroke survivors. Motor learning for stroke patients becomes greatly productive in robot-assisted gait training with real-time feedbacks such as motion interventions from a professional physical therapist [1], [2]. A physical therapist strives to successfully rehabilitate a stroke patient by observing whether the patient is safely using the robot and doing the intended movement with it [3]. However, in most cases, stroke survivors learn unstable and abnormal gait patterns due to muscle weakness and impaired movement coordination [4].

For the effective rehabilitation of patients, Khokhlova *et al.* carried out a study to distinguish normal and pathological gait using artificial intelligence and image sensors [5]. More specifically, they proposed a Long Short-Term Memory (LSTM) ensemble model to create an unsupervised gait classification tool based on computer vision technologies. Also, LSTM-based human gait stability predictor was presented using RGB-D and laser range finder data by Chalvatzake *et al.* [6]. The prediction algorithm of the stability of the patient's center of gravity was developed using an image sensor and Kalman filter to prevent the patient in the robot from falling over. Similarly, pose estimation for the elderly using Kinect was conducted [7]. Several human gait monitoring systems based on Inertial Measurement Units (IMU) have also been developed [8]. These systems have the equivalent performance of the current golden standard, Vicon, but there is potential for further development of applications that assist physical therapists in gait rehabilitation using the results of monitoring.

In this paper, we propose a real-time virtual coach to assist physical therapists with robot-assisted gait training using LSTM networks, which is practically applicable to rehabilitation training. We implemented a real-time virtual coach that proposes five coaching recommendations based on LSTM by utilizing time series data of inertial measurement units that are relatively small compared to image sensor data. Five LSTM networks were used to provide real-time coaching recommendations according to the patient kinematics. The coaching simulation was intentionally used to construct the LSTM network for gathering training data. The feasibility of proposed virtual coach including the evaluation of acquired data and observations of real-time implementation has been verified by five physical therapists. Therefore, our virtual coach can assist physical therapists in robot-assisted gait training in practice.

This paper is organized as follows. In Section II, we briefly highlight the implications of previous studies conducted by the National Rehabilitation Center (NRC) in the Republic of Korea. The concept of the proposed virtual coach is also presented in Section II. In Section III, the implementation of the proposed virtual coach is presented in detail. The implementation result of the proposed virtual coach is presented in Section IV. Five physical therapists were interviewed for the feasibility verification of the proposed virtual coach in Section IV. The conclusions and future works are given in Section V.

II. Virtual Coach for Robot-assisted Gait Training

A. Preliminary research

The role of physical therapist has become more significant in rehabilitation hospitals that use rehabilitation robots. NRC in the Republic of Korea, which is equipped with a variety of rehabilitation robots, has been performing studies on robot-assisted gait training for several years [9]. It is noteworthy that each rehabilitation robot, such as G-EO System and ErigoPro, has unique desired joint trajectories [10], [11]. The physical therapists have also provided various interventions

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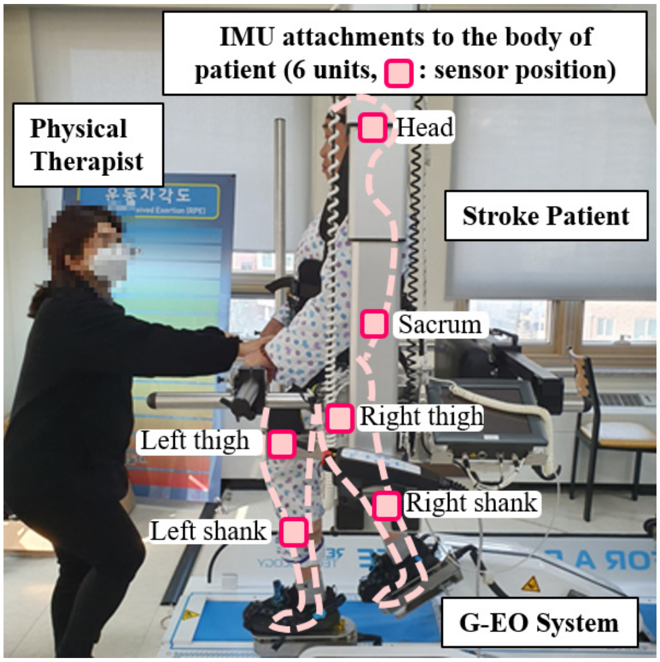


Fig. 1: Gait training of the stroke patient using G-EO System (Reha Technologies, AG, Olten, Switzerland) with six IMU attachments (6 units, sensor positions: head, sacrum, left thigh, right thigh, left shank, and right shank) to the body of the stroke patient, at the National Rehabilitation Center (NRC), Republic of Korea.

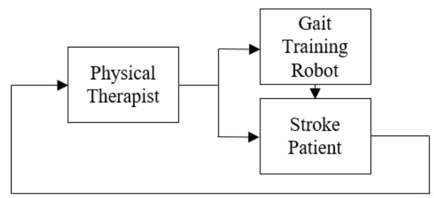
for a patient according to the characteristics of the rehabilitation robot. Table I shows the types and coaching count that occurred when using the G-EO System. A physical therapist would make more meaningful interventions or coaching recommendations in the G-EO System because, the high degree of freedom offered by the G-EO System is higher than that of the exoskeleton robot that directly restrains the joint of the patient. For a physical therapist to provide proper coaching, specialized gait rehabilitation knowledge and continuous patient monitoring are indispensable. The physical therapist should be able to understand robot characteristics and examine the human-robot interaction carefully. Therefore, high-level interventions or coaching by the physical therapists are required for effective or successful robot-assisted gait training for stroke survivors.

B. Concept of the proposed virtual coach

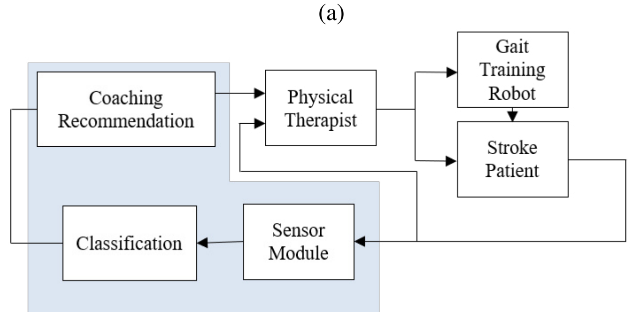
Based on the previous studies [10], [11] conducted by the NRC, the role of a physical therapist becomes more significant for encouraging a subject during end-effector-based robot-assisted gait training. Although existing physical/psychological burden on the physical therapist performing manual therapy has been meaningfully reduced by using rehabilitation robots, careful attention from physical therapists is still necessary for adequate intervention. A physical therapist should necessarily check whether a patient is using the rehabilitation robot safely and is operating it as per the design. For reducing the burden on a physical therapist and

TABLE I: Number of coaching instructions given by the physical therapist in robot-assisted gait training of stroke survivors using the G-EO System (Reha Technologies, AG, Olten, Switzerland) in 343 sessions of 23 patients. The count is the number of times a physical therapist has coached a patient. Each session lasted 30 min.

Coaching	Count	Ratio
Mid-line alignment	1108	31.68%
Knee flexion in preswing	803	22.96%
Trunk upright	549	15.70%
Head upright	299	8.55%
Heel strike in initial contact	251	7.18%
Knee extension in mid stance	163	4.66%
Trunk rotation alignment	157	4.49%
Heel strike in initial contact with visual feedback	95	2.72%
Plantar flexion in preswing	72	2.06%



(a)



(b)

Fig. 2: Concept of the proposed virtual coach on robot-assisted gait training (a) Conventional robot-assisted gait training, (b) Robot-assisted gait training with the proposed virtual coach.

improving the performance of robot-assisted gait training by providing supplementary information, we propose a virtual coach. The proposed virtual coach aims to analyze the state of a patient using the kinematic data from the sensor module and provide coaching recommendation to physical therapists to correct patient motion during gait training. As shown in Fig. 2a, in conventional robot-assisted gait training, physical therapists mainly observe the patient. The proposed virtual coach, which consists of the sensor module, the classification, and the coaching recommendation, is introduced as shown in Fig. 2b. The role of the sensor module is to gather patient kinematic data and to construct datasets for classification. In classification, the constructed datasets are analyzed using pre-defined classifiers. The coaching recommendation provides an appropriate recommendation based on

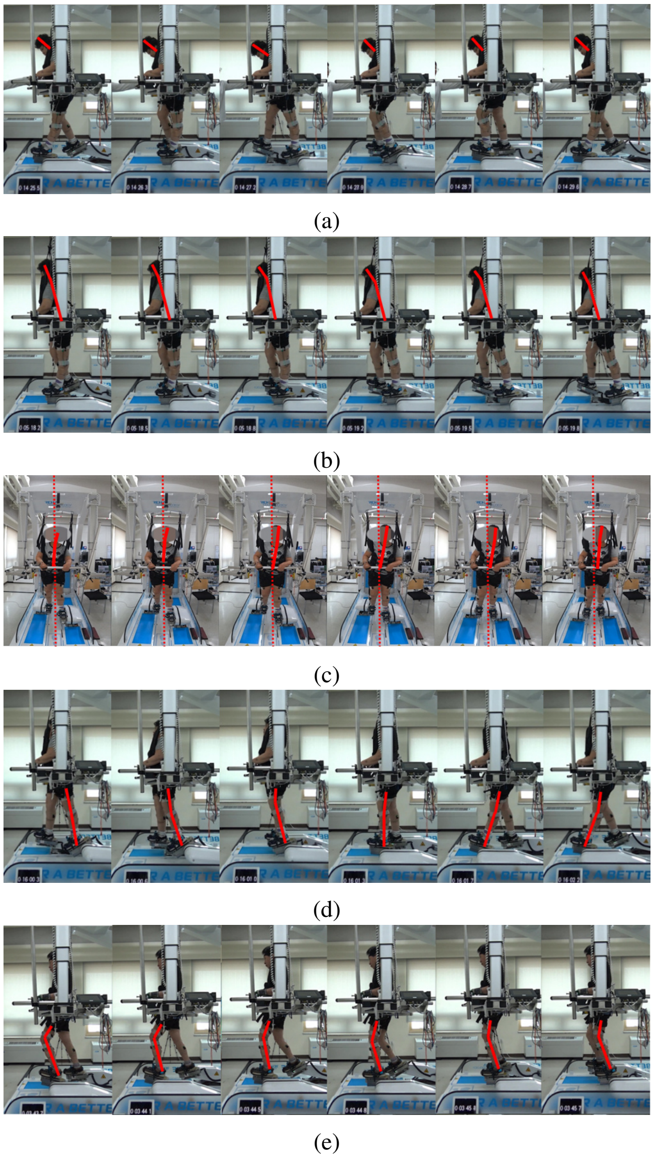


Fig. 3: Pathologic gait pattern in gait training using G-EO System, (a) Lack of head upright, (b) Lack of trunk upright, (c) Lack of mid-line alignment, (d) Lack of knee flexion in the swing phase, (e) Lack of knee extension in the mid-stance phase.

the classification. As shown in Fig. 2, a new concept of robot-assisted gait training is generated with the proposed virtual coach, thus reducing the burden on the physical therapist.

III. Implementation of the Proposed Virtual Coach

A. Selection of coaching recommendations

Our proposed virtual coach is designed to provide five coaching recommendations that are frequently used during the robot-assisted gait training for stroke survivors under the supervision of a professional physical therapist. It should be noted that the following five motions can be classified using the kinematic information as shown in Fig. 3. Heel strike in the initial contact with visual feedback requires ground contact sensors. Therefore, considering the results of Table I, required number of sensors, and the perspectives about normal gait from professional physical therapists, five coaching recommendations that are selected is as follows.

1) Head upright: Head upright is significant for maintaining the overall center of gravity of the patient with a strong relation to the motion of the patient. This is also selected because it is an essential factor that affects the level of concentration during the gait rehabilitation training.

2) Trunk upright: According to professional physical therapists, trunk bending occurs when muscles are weakened and rely too much on the robot safety bar during gait training. The trunk bending deteriorates the knee joint motion of the patient. Therefore, the trunk upright is selected.

3) Midline alignment: Most stroke patients have hemiplegia, so they do not hold the center of the body rigidly during robot-assisted gait training and is often biased to one side. Moreover, the midline alignment is a key factor in the clinical gait index, such as the Timed Up and Go test (TUG) [12]. The midline alignment is selected as corrective coaching because its misalignment causes an imbalance in the overall gait.

4) Knee flexion in the swing phase: Knee flexion in the swing phase is the main point due to the range of motion of knee and its strength on gait. Table I shows that many stroke patients had weakened muscles during clinical trials and were unable to perform proper knee flexion. Therefore, the knee flexion motion is selected.

5) Knee extension in the mid-stance phase: The knee extension in the mid-stance phase influences the range of motion and the muscle strength like the knee flexion in swing phase. Most stroke survivors had difficulty straightening their knees in the mid-stance phase.

B. Data gathering

Since the coaching recommendations are selected to be distinguishable using the kinematic data, a total of 6 IMUs are used in the proposed algorithm. The specifications of the sensor used are as follows: the accelerometer ranged $\pm$ 2 g, the gyroscope ranged $\pm$ 2000 deg/s, and the magnetometer ranged $\pm$ 49.7 Gauss [13]. The IMUs and the computer communicates via Bluetooth 4.0. The sensor locations are described in Fig. 1 and Fig. 5. Two IMUs are attached to the back of the head and the sacrum located at the waist, respectively. Four IMUs are attached on the outer part of each thigh and shank to measure joint angles. During the gait training, Velcro straps are fastened to minimize the vibration of the sensor.

C. Training for classification

1) Training datasets: We set a basic unit for the training dataset as 5 s for the time series data with labels because professional physical therapists make coaching recommendations after observing at least two or three cadences, which take about 3 to 5 s. It should be noted that the number of data generated from the robot-assisted gait training of

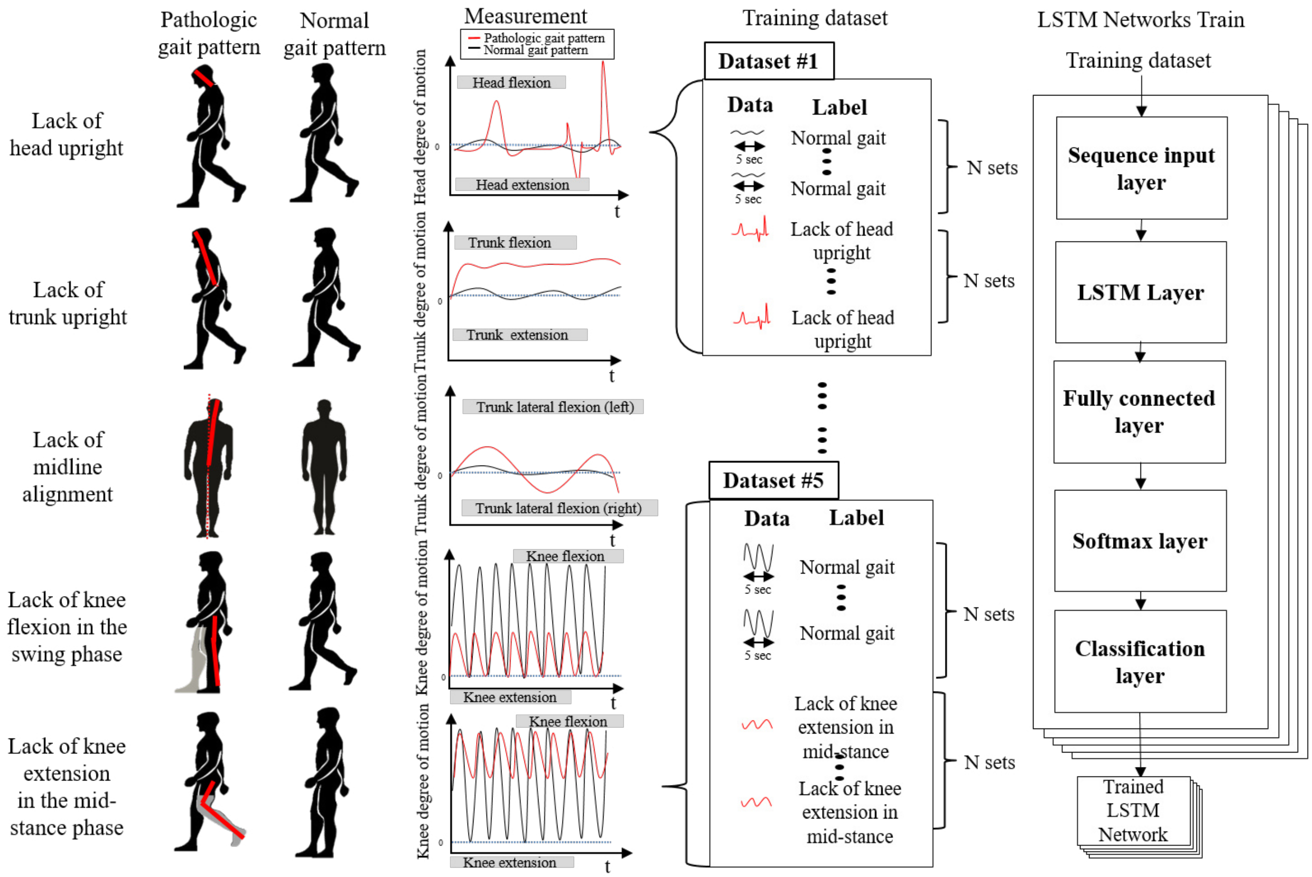


Fig. 4: Training structure for the proposed virtual coach. The pathological gait pattern selected above is shown. In addition, a comparison between pathological gait pattern and normal gait pattern in end-effector based robot-assisted gait training is exemplified. The simplified description of training datasets and the training structure of Long Short-Term Memory (LSTM) networks are presented.

23 stroke patients are not enough to apply for training the LSTM. Therefore, we created many pseudo pathological motion data by allowing an able-bodied person to simulate the pathologic gait of the patient continuously under the supervision of a professional therapist. The simulation of the pseudo pathologic gait of an able-bodied person is attached as a video attachment. The types of selected data are shown in Table II. In Table II, IMU data refer to the 3-axis accelerations, 3-axis angular velocities, and 3-axis magnetic fields. The joint angle denotes the 3-axis joint angles, and the absolute angle denotes the 3-axis absolute angles. As shown in Fig. 4, five datasets were constructed to provide five coaching recommendations. In each dataset, N denotes the number of gait data and is set to 10,000. In other word, each dataset for a coaching recommendation is composed of a group of 10,000 labeled time series data for 5 s of normal gait and pathologic gait.

2) Training and Selection of classifier: Fig. 4 illustrates the overall structure of the proposed virtual coach. In this paper, we apply an LSTM network for the classification of the five coaching recommendations. The complicated processes such as feature extraction in machine learning-based methods are avoided by using the deep learning-based method. Moreover, LSTM is highly specialized for processing time series data, and it is easy to expand using new training data obtained from clinical trials.

TABLE II: Dataset structure to provide each coaching recommendation.

Coaching recommendation	Dataset structure
Head upright	Head IMU data Head absolute and joint angle
Trunk upright	Sacrum IMU data Trunk absolute and joint angle
Midline alignment	Head, trunk, left/right hip and knee absolute and joint angle
Knee flexion in the swing phase	Left/right hip absolute and joint angle Left/right knee absolute and joint angle
Knee extension in the mid-stance phase	Left/right hip absolute and joint angle Left/right knee absolute and joint angle

LSTM networks are independently constructed because each coaching recommendation occur simultaneously. LSTM network training consists of a sequence input layer, an

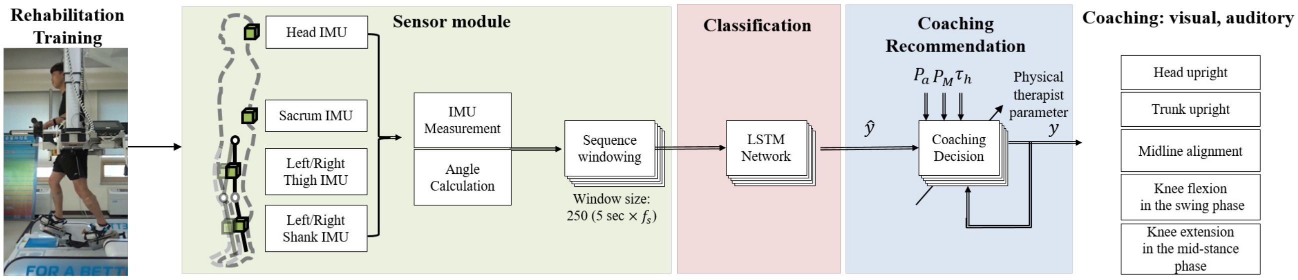


Fig. 5: Architecture of virtual coach in real-time.

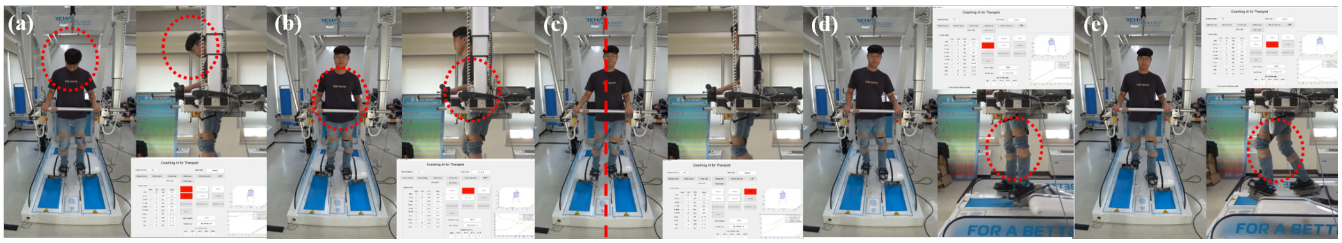


Fig. 6: Classification results for coaching recommendations (a) Head upright, (b) Trunk upright, (c) Midline alignment, (d) Knee flexion in the swing phase, (e) Knee extension in the mid-stance phase.

LSTM layer, a fully connected layer, a softmax layer, and a classification layer. In LSTM training, 70 % of the time series data in each dataset are used for training, while rest of it is used for verification. In view of accuracy, the LSTM achieved 99.7 % accuracy. For the performance comparison, typical Support Vector Machine (SVM) and k-Nearest Neighbor (kNN) algorithm were used, which were implemented using the machine learning toolbox from MATLAB 2019a. The identical training data were used. SVM and kNN showed mean accuracies of 88.8 % and 88.1 %, respectively. Therefore, LSTM network is chosen because of its suitability for time series data processing and shows an accuracy higher than other classification algorithms such as SVM and kNN. The training environments are set as follows. LSTM network trainings are performed using MATLAB. The GPU used for training is NVidia TITAN RTX. The number of hidden cells is 100, InitialLearnRate is 0.001, L2 regularization is 0.1, MaxEpoch is 10, GradientThreshold is 2, LearnRateDropFactor is set to 0.2, and LearnRateDropPeriod is set to 5. Through this training, five LSTM networks are derived for the classification of coaching recommendations.

D. Architecture of the proposed coach

Fig. 5 shows the architecture of the real-time virtual coach. The IMU data is acquired using 6 IMUs, and time series data for classification are constructed in the sensor module block. The sampling frequency (f_s) is set to 50 Hz, which is sufficient to contain human movements [14]. Through the sequence windowing block, gathered data are transformed into sequence data of 5-s durations, and then classified using the trained LSTM networks. In order to provide the coaching recommendation and reflect the characteristics of the physical therapist, three parameters are used, the level of activity of physical therapists, coaching probability margin, and coaching hold time. In the following description, index i is the selected coaching recommendation of Section II and k denotes the current time index. The level of activity of the physical therapist (Pa_i) refers to how often the therapist coaches. The probability margin of coaching (Pm_i) is the degree to which the coaching judgment is reserved. The coaching hold time (τ_i) is the minimum interval for coaching. The final coaching recommendation ($y_i(k)$) is determined by comparing the current coaching probability ($\lambda_i(k)$) and the recommended coaching threshold values ($\lambda_i(k)$). The current coaching probability is calculated as

$$p_i(k) = \frac{1}{N_w}\sum_{j=1}^{N_w} \hat{y}_i(k - N_w + j) \tag{1}$$

where $\hat{y}_(k)$ represents the output of the LSTM networks, and Pm_i denotes the number of sequences. The recommended coaching threshold values are derived as

$$\lambda_i(k) = \lambda_i(k-1) + P_M y_i(k-1) + \frac{p_{a,i}}{N_w}\sum_{j=1}^{N_w} e(k - N_w + j). \tag{2}$$

The final coaching recommendations are decided as

$$\begin{aligned} y_i(k) &= 0 \qquad \text{if } \lambda(k) \geq p_i(k) \\ y_i(m) &= 1 \qquad \text{if } \lambda(k) < p_i(k) \\ & m = k, k+1, ..., k + f_s\tau_i - 1 \end{aligned} \tag{3}$$

where m denotes an index used to maintain the final coaching recommendation for the coaching hold time.

IV. Experimental Verification

The results of coaching recommendations are presented to the physical therapist in the form of sound and visual

TABLE III: Accuracy of the LSTM network classification result.

Coaching recommendation	Correct case	Incorrect case	Data number	Accuracy
Head upright	117	0	117	100.00%
Trunk upright	109	3	112	97.32%
Midline alignment	85	20	105	80.95%
Knee flexion	99	5	104	95.19%
Knee extension	107	3	110	97.27%

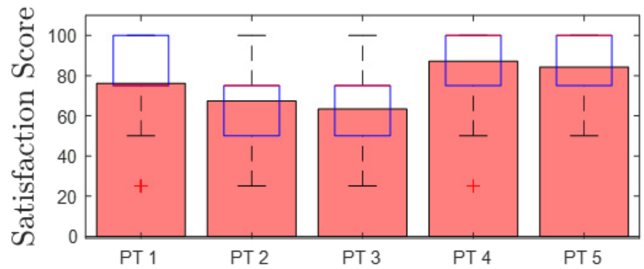


Fig. 7: Result of satisfaction score with the observation of the proposed virtual coach by five physical therapists.

graphs using the MATLAB Graphic User Interface (GUI). This GUI is implemented in Windows 10 with Intel i7-9900K CPU, and is configured to operate in real-time by using an external clock of National Instruments PCIe 6321. The classification performance of the proposed virtual coach is verified using the classification simulation of an able-bodied person on the rehabilitation robot, G-EO System, using the implemented GUI. As shown in Fig. 2, the proposed virtual coach corresponds to a kind of human-in-the-loop system because physical therapist's coaching and the patient are included in the block diagram of the robot-assisted gait training with the proposed virtual coach. Therefore, it was confirmed whether our proposed virtual coach provides proper coaching in an adequate time when an able-bodied person intentionally performs the pathologic gait motion that requires coaching under supervision of a professional physical therapist. The results are shown in Table III and Fig. 7. Looking at the results in Table III, we found that the coaching recommendation had an accuracy of over 95 percent, except for mid-alignment with about 80 percent accuracy. In addition to these results, five therapists underwent satisfaction surveys to observe the robot-assisted gait training with our proposed virtual coach. As shown in Fig. 7, the results of the satisfaction score were 76.16, 67.44, 63.37, 87.20, and 84.30. The survey information was attached to the video.

V. Conclusions and Future Works

We propose a virtual coach to assist the physical therapist. The proposed virtual coach was able to provide coaching recommendations, which are frequently used during the robot-assisted gait training, according to the inclination of physical therapist using LSTM networks in real-time. The state of the patient was clearly identifiable. Finally, the proposed virtual coach assisted the professional physical therapists to increase the efficiency of gait training and enable safer and systematic rehabilitation training. Since our virtual coach is implemented using IMUs and GUI, training is required for the hardware and software operations. The safe and proper method of donning and doffing of IMUs for stroke patients must also be provided. Since the virtual coach is dependent on the sensor measurement accuracy, the operation status of sensors must be verified. The training dataset must be improved by deriving and updating it with clinical trials of stroke patients.

Since this study aims to assist physical therapists, more clinical feasibility studies are necessary. Our further studies will include: improved classification accuracy of coaching recommendations, more coaching recommendations, clear evaluation of the human-in-the-loop-system, clinical study for the effectiveness of the proposed virtual coach, and constructing an add-on safety monitoring module to prevent unexpected operations.

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