Vision-based human joint angular velocity estimation during squat and walking on a treadmill actions

Konki Sravan Kumar¹, Ankhzaya Jamsarndorj², Dawoon Jung¹, Daehyun Lee³, Jinwook Kim¹ and Kyung-Ryoul Mun¹

Abstract—Elderly health monitoring, rehabilitation training, and sport supervision could benefit from continuous assessment of joint angle, and angular velocity to identify the joint movement patterns. However, most of the measurement systems are designed based on special kinematic sensors to estimate angular velocities. The study aims to measure the lower limb joint angular velocity based on a 2D vision camera system during squat and walking on treadmill action using deep convolution neural network (CNN) architecture. Experiments were conducted on 12 healthy adults, and six digital cameras were used to capture the videos of the participant actions in lateral and frontal view. The normalized cross-correlation (Ccₙ₉₀) analysis was performed to obtain a degree of symmetry of the ground truth and estimated angular velocity waveform patterns. Mean Ccₙ₉₀ for angular velocity estimation by deep CNN model has higher than 0.90 in walking on the treadmill and 0.89 in squat action. Furthermore, joint-wise angular velocities at the hip, knee, and ankle joints were observed and compared. The proposed system gets higher estimation performance under the lateral view and the frontal view of the camera. This study potentially eliminates the requirement of wearable sensors and proves the applicability of using video-based system to measure joint angular velocities during squat and walking on a treadmill actions.

I. INTRODUCTION

Estimation of lower limb Kinematics such as joint angular velocity is a significant clinical parameter that can help to assist elderly daily walking [1, 2] determine the progress during the rehabilitation of patients [3], improve athletes performance [4, 5], enhance human health, develop the sports gear equipment, diagnose early human joint movement disorders and recognize human activity [6]. Wearable sensor-based systems typically measure joint angular velocity. Wearable sensor-based systems employ sensors attached to human joints to extract joint movement information. Inertial measurement units (IMU) such as accelerometers, gyroscopes and magnetometers are effective, practical and powerful tools for human angle estimation and angular velocity measurements, drawing much attention from researchers [7–10]. The IMU sensors have been widely used as an alternative to the optoelectronic motion capture system, a gold standard for human joint kinematics measurements and showed sufficient reliability. However, one IMU sensor can only measure one body segment’s motion, so usually, seven IMU sensors are required just for a lower limb motion such as pelvis, ankle, knee, and hip of each left and right side. When many IMU sensors are used, complex preprocessing processes such as sensor-to-segment calibration, subject calibration, and human kinematic chains should be considered to measure accurate joint kinematics. In addition, the use of motion tracking systems like IMU sensors hinder the natural movements of the subjects due to tight straps for the sensor attachment, and it is still expensive, complex handling of equipment, power consumption, participant cooperation and controlled laboratory restrictions [11]. To mitigate the limitations of wearable sensor-based measurement systems, novel vision-based systems were used to estimate human low limb kinematics. Recently emerged deep learning frameworks had opened a new possibility of human joint angle estimation from images captured by RGB-D cameras [12]. However, the Kinect depth image database suffers from sparse and noise. A 2D single-camera gait kinematics analysis system has been proposed in [13] to measure the knee angle. Estimate the joint angle from extracted center coordinates of the marker. But, marker tracker can only track the makers on camera facing lower limbs. It may not track the marker on the other views. Conversely, a marker-less system based on the OpenPose library was introduced for gait analysis [14, 15]. However, joint angles were extracted from the OpenPose algorithm based on the 2D keypoint datasets that are manually annotated and annotated keypoints are not center of the joint. Therefore, it may not be reliable to estimate angular velocity based on the Openpose library. The marker-less systems, which were mentioned above, can estimate the joint angles, but these were designed to track the participants only in side view of a camera, unable to distinguish between the lateral and frontal view (not view-invariant) and lacks in the adequate accuracy in joint angle estimation. Therefore, the motivation of the study was to design a view-invariant system for accurate joint angular velocity estimation.

This paper proposes a video-based joint angular velocity estimation system using deep learning techniques. In particular, we focused on estimating six joint angular velocities of the three joints located on the right and the left side of human lower limbs. In joint angular velocity measurement during daily life actions, videos of a healthy adult were acquired using digital cameras during squat and walking on treadmill actions. Estimation results of the proposed architecture were analyzed and compared with ground truth angular velocities tracked by the motion analysis system.
II. METHODS

A. Experimental Configuration

To collect the dataset, experiments were performed in an experimental room installed with the motion analysis system, which has 8 optical cameras and a frequency of 120Hz. It tracks markers attached to the human body’s lower limbs according to the Plug-in-gait marker set and carries out the accurate angular velocity of all joints during the experiments. The angular velocity is calculated by derivation of the angles. Fifteen markers were placed on the left and right side of the hip, knee and ankle joint to capture the lower body motion, as shown in Fig. 1. Xiaomi mijia 4K system has 6 digital cameras with a frame rate of 60Hz, and a resolution of 1920×1080 was used to capture videos of 12 healthy adults during squat and walking on treadmill actions within 30 seconds. There are four cameras placed in front, and two cameras were located on the side of a participant with the capture area has a size of 2.000 meters by 3.685 meters on the floor, as shown in Fig. 1. We designed a circuit to receive the flash signal from a flash device to synchronize digital cameras and optical cameras. When the flash fires, a photodiode will generate an electric current. An operational amplifier converts the small amount of current to the Transistor–transistor Logic (TTL) level signal. When the signal changes abruptly, the microcontroller (Arduino Nano) will generate pulses lasting in 100ms. The motion capture system which was used in this experiment is triggered a rising edge pulse. Furthermore, the digital cameras will capture the flashing moment. Hence, this signal was used to cut videos corresponding to actions and subjects. We calculated the average intensity of pixels in each frame, plotted them and find a threshold for flashing frames. Lastly, we down-sampled the frame rate of annotations from 120Hz to 60Hz because the frequency of optical cameras is twice the value for digital cameras.

B. Joint angular velocity estimation based on deep learning architecture

In this section, we presented in detail the joint angular velocity estimation system. The framework of the proposed architecture is shown in Fig. 2. We built a joint angular velocity estimator to simultaneously estimate the joint angular velocities at hips, knees, and ankles on both the right and left sides. A sequence of 9 lateral or frontal-view video frames during the action as features and the corresponding target joint angular velocities are fed to the deep-learning networks in a supervised manner. Initially, we employed a 4th version of the YOLO (You Only Look Once) object detection algorithm to detect the human in the action videos [16]. Subsequently, the images from videos were cropped based on resultant human bounding box detection by the YOLO algorithm and then padded depending on the bounding box’s size to obtain a uniform square image in action videos. Finally, the padded images were resized to a size of 448 x 448. In this study, we employ three deep convolutional neural networks modified from Densenet121, ResNet18, ResNet50 architectures [17] to address the problem of joint angular velocity estimation. To make the network appropriate for our problem, we replaced the last fully connected (FC) layer with six neurons. The six neurons correspond to all the six joint angular velocities such as left/ right hip flexion/extension, knee flexion/extension, and ankle dorsiflexion/plantarflexion.

C. Network implementation and training scheme

The proposed deep CNN networks were implemented using the PyTorch deep learning open-source library in Python with the mean absolute error (MAE) as the loss function and Adaptive Moment Estimation (Adam) for optimization on a PC configured with an Intel® Core™ i7-9700 CPU at 3.00 GHz x 8, using Ubuntu 18.04.5 LTS. The Densenet121 model was first trained on the ImageNet dataset [18] and then utilized the pre-trained model to initialize the joint angular velocity estimation network. We choose a learning rate of 0.0001, batch size of 8, dropout probability at the last layer as 0.5 and trained a network using a stack of 9 consequent video frames with corresponding ground truth angular velocities in 20 epochs. There are videos of six healthy subjects during a squat and walking on a treadmill, intended for training, videos of three healthy subjects for validation and three healthy subjects for testing. This new dataset contains 203160 frames, 106920 for training, 48120 for validation and 48120 for testing.

III. EXPERIMENTAL RESULTS

This section demonstrates detailed explanations of experimental results to estimate joint angular velocity using deep learning architectures. The ground-truth and the estimated joint angular velocities at the hip, knee, and ankle joint by the different deep CNN architectures as shown in Fig. 3. The estimated results for joint angular velocities at the hip, knee, and ankle joint during squat action are displayed in Fig. 4. From Fig. 3 and Fig. 4, we have noticed that proposed deep CNN models show good angular velocity estimation.
To perform the quantitative analysis, we calculated Normalized cross-correlation [19] for angular velocity estimation using deep CNN models during squat and walking on a treadmill as presented. $C_{c_{norm}}$ analysis for the joint-wise angular velocities is used to obtain a degree of symmetry of the ground truth and estimated angular velocity waveform patterns. Average $C_{c_{norm}}$ of angular velocities using three deep CNN models as presented in Table I. DenseNet121 model produces higher $C_{c_{norm}}$ of 0.89 and 0.91 during squat and walking on a treadmill, respectively.

An average $C_{c_{norm}}$ for the joint-wise angular velocity at hip, knee and ankle during walking on a treadmill was estimated using different deep CNN architectures as shown in Fig. 5 and in Table II. DenseNet121 model produces higher $C_{c_{norm}}$ of 0.87, 0.95 and 0.86 at hip, knee and ankle joint, respectively. Fig. 6 and Tables III illustrates an average $C_{c_{norm}}$ of angular velocities at hip, knee and ankle joint during squat were estimated using different deep CNN architectures. The mean $C_{c_{norm}}$ for angular velocity estimation under different camera views is demonstrated in Table IV. An average $C_{c_{norm}}$ for side and front view are 0.90 and 0.87, respectively.

**TABLE I:** An average $C_{c_{norm}}$ for estimated angular velocities during squat and walking on a treadmill by deep CNN architectures.

<table>
<thead>
<tr>
<th>Model</th>
<th>Squat</th>
<th>Walking on treadmill</th>
</tr>
</thead>
<tbody>
<tr>
<td>ResNet18</td>
<td>0.87</td>
<td>0.90</td>
</tr>
<tr>
<td>ResNet50</td>
<td>0.88</td>
<td>0.90</td>
</tr>
<tr>
<td>DenseNet121</td>
<td>0.89</td>
<td>0.91</td>
</tr>
</tbody>
</table>

**TABLE II:** An average $C_{c_{norm}}$ analysis of joint wise angular velocities at hip, knee and ankle joint during walking on a treadmill.

<table>
<thead>
<tr>
<th>Model</th>
<th>Hip Joint</th>
<th>Knee Joint</th>
<th>Ankle Joint</th>
</tr>
</thead>
<tbody>
<tr>
<td>ResNet18</td>
<td>0.80</td>
<td>0.94</td>
<td>0.84</td>
</tr>
<tr>
<td>ResNet50</td>
<td>0.85</td>
<td>0.94</td>
<td>0.84</td>
</tr>
<tr>
<td>DenseNet121</td>
<td>0.87</td>
<td>0.95</td>
<td>0.86</td>
</tr>
</tbody>
</table>
To evaluate the accuracy of the proposed models, we compare the results in terms of MAE for joint-wise angular velocity during squat and walking on a treadmill action. The deep CNN models are trained by action video frames features and corresponding target angular velocity of joints. This proposed system can estimate the joint angular velocity of the hip flexion/extension, the knee flexion/extension, and the ankle dorsiflexion/plantarflexion without the use of any wearable sensors. The estimated joint angular velocities and ground truths were graphically compared to investigate the estimation performance of deep CNN models as shown in Fig. 3 and Fig. 4. Estimated angular velocities well follow its ground truth profile during both actions. Estimation accuracies of all deep CNN models were evaluated using the $C_{\text{norm}}$ and MAE. $C_{\text{norm}}$ measures the degree of symmetry of the ground truth, and estimated angular velocities. $C_{\text{norm}}$ computation generates the values range from 0 to 1, and a $C_{\text{norm}}$ value close to 1 shows that both ground truth and estimated angular velocity have strong symmetry. Estimated angular velocities of all deep CNN models were highly correlated with ground truth. However, DenseNet121 model reports better estimation with more than 0.90 average $C_{\text{norm}}$ in walking on a treadmill and 0.89 during squat actions as presented in Table I. The performance of the proposed models was further investigated based on the hip, knee, and ankle joint angular velocity. As shown in Fig. 5 and Table II, DenseNet121 model depicts a better average $C_{\text{norm}}$ of three joints during walking on a treadmill action. Furthermore, the knee joint shows a higher correlation of 0.95. Similarly, DenseNet121 model gets higher accuracies than other models and knee joint reported better estimation with 0.93 during squat action as shown in Fig. 6 and Table III. It was indicated that the knee joint gets higher estimation than hip and ankle joints. The knee joint has more stable
ground truth angular velocity, ankle joint having a higher degree of freedom, the hip joint estimation accuracy may affect by variations in human body size of subjects, and motion artifacts due to the fluctuations of the marker at the hip joint. As reported in Table IV, the mean Cc_{norm} in lateral and frontal view is about 0.90, indicating that the proposed system maintains relatively higher estimation accuracy in both camera views. Table V and Table VI demonstrate the MAE of all three joint-wise angular velocities estimated by ResNet18, ResNet50 and DenseNet121. We can notice that MAE for DenseNet121 exhibits lesser than ResNet18, ResNet50. However, all these deep CNN methods still showing higher error due to time delay in the estimation results, and an offset value error can be generated from the imprecise positions of makers on the human body, and the human body size and shape variation within the subjects. In our future work, the proposed pre-trained CNN model will be extended to use of complex recurrent, attention networks to obtain a temporal information for more stable angular velocity estimation over time. Furthermore, a larger dataset with numerous daily life actions and different age groups of subjects with gait pathologies is needed to evaluate the practical performance.

V. CONCLUSIONS

This study presents a vision-based angular velocity estimation system using deep learning techniques to estimate the lower limb joint angular velocities during a squat and walking on a treadmill action. The main contribution of this paper is to employ a modified deep CNN architecture to measure the joint angular velocity of the hip, knee, and ankle joints. Additionally, we constructed a new dataset of walking on a treadmill and squat action. The deep CNN models are trained by action videos frames features and corresponding target angular velocity of joints. This proposed estimation system offers good estimation accuracy under different camera view angles. Our preliminary study has proven the applicability of using action video to estimate angular velocity based on CNN. However, this vision-based system is still showing higher MAE errors due to time delays in estimations. Therefore, the proposed pre-trained CNN model will be extended to use of complex recurrent, attention networks to obtain a temporal information for more stable angular velocity estimation over time.

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