A Novel Sparse-IMU Convolutional Neural Network for Real-Time Hip Kinematics in Exoskeleton-Augmented Gait

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Personal Section

It all started with an appreciation for the ways that artificial intelligence can be applied in improving health outcomes. While in high school, I looked for many chances to combine medicine, data science, and engineering in order to find solutions for real-world problems using computational approaches.

The first research project I have taken part in was related to ophthalmology at the University of California, Irvine. Specifically, at the Gavin Herbert Eye Institute, I helped develop the image analysis methods to evaluate the density of corneal endothelial cells from microscopic pictures of eyes. By comparing the traditional manual approach to the semi-automatic image processing one, I saw the possibilities that computational approaches can bring to medicine in terms of speed, accuracy, and reliability. Moreover, it allowed me to see how artificial intelligence and computer vision can assist doctors in transforming the information about complex visual pictures into useful data. However, I also became interested in applying artificial intelligence to solve complex medical problems in a more tangible way using engineering. It happened when I took part in the GSTEM program at New York University and performed research at the Biomechatronics and Intelligent Robotics Laboratory.

Before entering the lab, I had no idea about rehabilitation robotics. Having started analyzing scientific literature on mobility disorders, I understood how widespread this problem is; millions of people suffer from strokes, spinal cord injuries, Parkinson's disease, multiple sclerosis, and other neurological disorders, which seriously impede their independent movement. But it was the idea of wearable robotic exoskeletons that caught my eye. As opposed to diagnostic systems, designed to diagnose and monitor patients' health conditions, exoskeletons aim at helping their users move and stand. What really interests me about this topic is the opportunity for the patient to gain newfound independence and control over their actions, without any need for caregivers or devices. To be able to move freely, make decisions, and take part in various activities is something we usually do not value until we've lost it. Moreover, in my own personal experience, seeing my grandmother suffering from osteoarthritis and requiring a knee replacement surgery, I came to understand how tragic the loss of mobility can be in someone's life. Routine tasks were now becoming things that needed aid and rehabilitation. Seeing all of this further demonstrated the importance of rehabilitative technologies, and for this reason, I was incredibly excited to undertake a project on wearable robotics and exoskeletons.

Research Section

Abstract

Wearable robotic exoskeletons are assistive devices designed to support human movement, especially for individuals undergoing rehabilitation or living with mobility impairments. For these devices to operate safely and effectively, they must be able to estimate how the user's joints are moving in real time. One important measurement is sagittal-plane hip flexion, which describes the forward and backward bending motion of the hip during walking. Current systems often rely on full-body inertial measurement unit (IMU) arrays or laboratory motion capture systems to estimate joint motion. Although these systems can be accurate, they are also expensive, time-consuming to set up, and uncomfortable for long-term use. This study investigated whether a reduced-sensor configuration using only bilateral thigh-mounted IMUs could predict hip joint angles with accuracy comparable to a full-body IMU configuration. Healthy adult participants walked on a treadmill under two conditions: baseline walking without an exoskeleton and walking while wearing a powered hip exoskeleton. IMU signals were collected from the lower spine, pelvis, thighs, shins, and feet, while ground-truth hip flexion angles were exported from the Noraxon MyoMotion system. A convolutional neural network (CNN) was trained to predict near-future hip flexion angles from short windows of sensor data. The model was tested under both full-body and thigh-only sensor configurations. Performance was evaluated using root mean square error (RMSE), Pearson correlation coefficient, Cohen's d, and Bland–Altman agreement analysis. The thigh-only model achieved a mean RMSE of 3.07° during unassisted walking, only 0.24° higher than the full-body model's 2.83° RMSE. During exoskeleton-assisted walking, the thigh-only model achieved 3.97° RMSE compared to 3.47° for the full-body model. Across all conditions, correlations remained high, suggesting strong agreement between predicted and true hip angles. These findings suggest that sparse IMU configurations may provide a practical alternative to full-body sensing systems for real-time hip kinematics estimation in wearable robotics and rehabilitation.

1. Introduction

The traditional methods of calculating lower extremity movements include full-body IMUs or motion capture using cameras. Motion capture technique offers high accuracy, but it demands the usage of cameras, reflective markers, lighting, and special lab equipment. A full-body IMU system is convenient but still uses several sensors that should be fixed on different parts of the body, such as the pelvis, lumbar spine, thighs, shins, and feet. Although the use of multiple sensors allows gathering much information about the human movement, it makes this technique more expensive and time-consuming, and may reduce users' comfort. It is important to mention that for people with neurological or neuromuscular disorders, comfort and ease of use of the device are essential factors. If something is hard to wear and to set up, then it will probably never be used. That is why I decided to find out whether the use of thigh-only IMUs with a CNN can provide results similar to a full-body IMU system. Given that the sensors on the thighs can provide sufficient data about hip motion, then in future designs of exoskeletons, there might be ways of minimizing the number of sensors needed in the system without compromising its accuracy. Not only did I aim to analyze different sensor arrangements, but I also strived to investigate the effects of exoskeleton power assistance on gait prediction accuracy.

2. Background

IMU is a sensor worn on a part of the body and measures motion in terms of accelerations, angular velocities, and magnetic field strength with the help of accelerometers, gyroscopes, and magnetometers. In this way, signals from accelerometers, gyroscopes, and magnetometers combined could be used to describe the movement of a body part. In our case, each IMU gathered tri-axial data measured by accelerometer, gyroscope, and magnetometer. Our main dependent variable was the sagittal-plane hip flexion angle. A sagittal plane cuts the body vertically into left and right parts, and motions in this plane include any forward or backward movements. Flexion of the hip joint is defined as the bending of the thigh bone in relation to the pelvis, for example, lifting up the leg during walking. As it happens continuously within the gait cycle, this problem cannot be treated as a classification problem where the goal is to identify the type of activity done, for example, “walking” or “standing.” Here, the model should predict a continuous value, which would be the hip angle in degrees. The term “time-series” is used to denote the sequential order of data in which each data value depends upon some other previous data values. “Regression” refers to the process of predicting a real-value target attribute rather than predicting a categorical value. If one predicts whether a person is walking or running, then it will be called a classification problem, but predicting the hip angle to be 28.4 degrees is a regression problem.

3. Methodology

IMU data were acquired from healthy adult subjects undergoing treadmill walking. Each subject undertook two sessions of 10-min walking trials at a constant velocity of 3.0 mph on a NordicTrack T 6.5 Si treadmill. For the first session, subjects performed treadmill walking in the absence of any exoskeleton assistance, which was denoted as the No Exo condition. For the second session, subjects performed treadmill walking while being equipped with Hypershell Go X powered hip exoskeleton, which was denoted as the With Exo condition. The exoskeleton is a hip-assistable wearable device that generates active torques at the hip joint to enhance gait.

Each subject was outfitted with Noraxon MyoMotion IMUs at seven anatomical points: lower spine, pelvis, left thigh, right thigh, left shin, right shin, left foot, and right foot. Each sensor captured accelerometer, gyroscope, and magnetometer data at a frequency of 200 Hz. This frequency of 200 Hz indicates that 200 data samples were taken each second. Ground-truth sagittal-plane hip flexion angles for the left leg and right leg were exported from the Noraxon MyoMotion software and served as the prediction targets for model training.

Prior to training the model, it was necessary to preprocess the raw IMU data. Because participants naturally differed in gait patterns, range of motion, and sensor signal magnitude, z-score normalization was applied to each participant's dataset. The process involves subtracting the mean of each sample and dividing it by the standard deviation. In other words, z-score normalization minimizes inter-subject variability, ensuring that the model focuses on underlying kinematic relationships rather than confounding differences in gait mechanics, range of motion, or sensor signal amplitude. After that, sliding windows were applied in order to cut the stream of continuous IMU data into separate windows. The length of each input window was 0.2 seconds, that is 40 samples at the frequency of 200 Hz of sampling. The stride was 0.1 seconds (20 samples), so the windows overlapped, and the temporal resolution of the data was preserved as well as the possibility for the model to learn the continuous walking pattern. The window was labelled by the average value of hip flexion angle during 0.05 seconds forecast horizon right after the input window. The machine learning algorithm chosen for prediction was a two-dimensional CNN implemented with the help of TensorFlow and Keras library. In the case of the thigh-only model, each input sample is represented as a two-dimensional tensor of 40 time steps and 18 features. The 18 features came from the bilateral thigh sensors, with each thigh contributing accelerometer, gyroscope, and magnetometer measurements across three axes. Two convolutional layers were employed in the CNN network, each having 128 and 64 filters, respectively. Both of these layers used 3×3 kernels and had ReLU activation functions. Convolutional layers aim at extracting local spatial-temporal patterns within the input data. This was followed by a 2×2 max pooling layer that aims at lowering the dimensionality of the input and reducing complexity. This was followed by flattening the feature map and feeding it into two dense layers with 128 and 64 neurons. The use of dropout and batch normalization was applied to mitigate the problem of overfitting. Overfitting is the situation where a machine learning model can perfectly predict its training set but not generalize. Dropout helps mitigate this by ignoring random neurons during training to encourage the development of better features. Batch Normalization helps in stabilizing the training process through normalization of intermediate values in the model. A single output neuron with linear activation was used to produce predictions of the hip flexion angle. For training, the Adam optimizer was used at a learning rate of 0.001 along with mean squared error as the loss function. Mean squared error is a measure of the average of the squares of the differences between predicted and actual hip angles. It is the process of squaring that makes the model concentrate on reducing large prediction errors since larger errors will have a higher penalty than smaller ones. Therefore, mean squared error was chosen as an appropriate loss function for training the regression model to make continuous predictions of hip flexion angles.

4. Results

The thigh-only CNN model performed almost equally as well compared to the full-body CNN model. For unassisted walking, the mean RMSE generated by the thigh-only CNN model was 3.07° while that of the full-body model was 2.83°. In other words, the removal of five sensors resulted in an average increase in prediction error of 0.24° for the No Exo condition. During exoskeleton-assisted walking, the mean RMSE generated by the thigh-only CNN model was 3.97° while that of the full-body model was 3.47°.

All configurations and walking modes resulted in high Pearson correlation coefficients, where the correlation value was $r \geq 0.937$. This shows a good match between the hip angles calculated and ground truth data. Despite a slight RMSE increase in the thigh-only configuration, the general hip angle movement trend was correctly estimated. The statistical analysis of configurations showed a Cohen's d value of 0.86, which corresponds to a large effect size. Though this means that the difference between configurations is not too large on a general level, fit might be significant for some participants. The Pearson correlation coefficient between RMSEs from configurations was found to be $r = 0.942$ ($r^2 = 0.887$). This shows a very good agreement between performance patterns of the two configurations.

The Bland-Altman analysis confirmed a strong agreement between configurations. The average difference between predictions in the two configurations was found to be +0.213°, with limits of agreement ranging from −0.274° to +0.701°. This narrow range demonstrates a high degree of agreement between the thigh-only and full-body configurations, indicating that the reduced-sensor approach remained a reliable proxy for the full-body model despite using substantially less input data.

Another significant finding was the increase in the prediction error when the participants walked with the exoskeleton-assisted walking for both sensor configurations. That means that the powered assistance created extra complexity in the movement pattern. It is possible that the exoskeleton affected the natural movement of the joint by changing its torque, neuromuscular control, or adaptation of the movement strategies, which, in turn, increased the randomness of the movement and RMSE in the With Exo condition. Comparison of the hip flexion and thigh flexion via the angle-angle plot confirmed the difference. The gait patterns in the unassisted walking looked smaller and more compact than the assisted ones, which indicated more regular and consistent joint movement.

There were small left-right asymmetries observed, mostly in the Exo condition. For instance, one of the participants had a higher RMSE on the right side when the participant walked with the exoskeleton. These asymmetries may reflect limb dominance, uneven device engagement, or compensatory motor strategies. Although these findings were not statistically significant, they suggest that future exoskeleton control systems may benefit from limb-specific or user-specific adaptation.

5. Discussion

The primary discovery from this study is that a bilateral thigh-only IMU arrangement can estimate hip flexion angle in the sagittal plane with accuracy that is on par with a full-body IMU arrangement if used in conjunction with a CNN. The finding backs up the initial hypothesis about the possibility of estimating hip angle kinematics with high accuracy without extensive use of body sensors. While the full-body configuration yielded higher accuracy, the margin by which it was higher is insignificant and demonstrates that bilateral thigh sensors can capture almost all information necessary for hip angle estimation. This finding is significant since it breaks the stereotype that more sensors always mean better results. Wearable robotics usually face the dilemma of choosing between usability and accuracy, as a fuller body sensor arrangement will contain more information, but at the same time it will take more time to configure, cost more, be harder to calibrate, and cause additional discomfort for users.

From the biomechanical perspective, it is logical that the model with only the thigh sensors is feasible, since this particular body segment participates in the movement of the hip joint. During walking, signals from the thigh sensors contain information about gait phase, leg swing and hip joint movement. Therefore, the CNN managed to find the relationship between these features in the IMU signals and translate it into the continuous hip angle prediction. It shows how useful it is to combine intuition about biomechanics with machine learning approach. The increased RMSE values during exoskeleton-assisted walking are also informative in terms of the influence of such a device on the gait. While exoskeletons are meant to assist the movement, the device is also likely to change the normal dynamics of walking. In case when the torque is applied to the hip, users may adapt their strides, joint coordination and muscle activation to the device in various ways.

This finding has some implications for future design of exoskeleton control systems. Models that only use normal gaits for training may not work well when predicting assisted gait. Exoskeleton systems used in real life would probably benefit from having adaptive algorithms that can be constantly improved as the patient gets used to the exoskeleton system. The hybrid deep learning approaches like CNN-LSTM, CNN-GRU, and transformers might also prove to be more effective because they take into consideration the temporal dependencies of gait better than traditional CNNs. Although CNN is good at detecting local patterns, gait is a time-series problem.

Left-right asymmetries detected in this study suggest the necessity for developing personalized models. In healthy subjects, small asymmetry may be caused by limb dominance or by the difference in fit between the two sides of an exoskeleton device. However, asymmetries found in the patients' group are likely to be more significant. It is known that stroke survivors, people who suffer from Parkinson's disease, and those with orthopedic injury usually have asymmetric gait patterns. Therefore, a model that assumes similar behavior of both sides might not work well in practice.

6. Conclusion

In summary, the proposed study showed that the estimation of sagittal plane hip joint angle with the help of a CNN model was possible with the usage of only thigh-mounted IMUs, and that this estimation had similar accuracy compared with the one obtained with the full body IMU placement. The RMSE values of estimation in normal walking were only 0.24° larger than those obtained with the full-body model, whereas the correlation with the ground truth hip joint angles was still high.

The primary significance of this work lies in demonstrating that accurate hip kinematic estimation can be achieved with a substantially reduced sensor configuration. Reducing the number of IMUs may result in reduced costs for the device, decreased calibration time, increased user comfort, and simplified installation procedure. All these benefits together might make exoskeleton-assisted rehabilitation more feasible.

To summarize, this work shows that good engineering does not necessarily involve increasing the number of elements or gathering additional data. The task frequently is to determine what is the minimal amount of data required to have accurate performance. With the help of sparse sensing, machine learning, and biomechanics, future exoskeletons might be cheaper, more available, and still highly accurate.