Estimation of Knee Adduction Moment Using Wearable Sensor with AI and Possible Adversarial Example

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Abstract: The knee joint is most commonly affected by osteoarthritis. Cartilage in the knee begins to break down after sustained stress, leaving the bones rubbing against each other and resulting in osteoarthritis. Nearly a third of US citizens are affected by knee osteoarthritis by age 70. Greater adduction moment at the knee during activities contributes to the high risk of knee osteoarthritis. However, the estimation of knee adduction moment is restricted in the lab environment. Using LSTM with the data from wearable sensors to predict knee adduction moments could be a feasible solution in a clinical environment. Moreover, the stability of the specific LSTM model should also be addressed.

Introduction

Knee osteoarthritis is a common condition that affects millions of people worldwide. It is a degenerative disease that affects the cartilage in the knee joint, causing pain, stiffness, and reduced mobility. This condition typically affects older adults but can also affect younger individuals who have had a knee injury or engage in activities that put excessive stress on the knee joint. Unfortunately, there is no direct cure medicine for knee osteoarthritis, and the condition tends to worsen over time. Knee osteoarthritis not only causes pain and discomfort but can also increase the economic burden on individuals, families, and healthcare systems. As the condition progresses, it may require more invasive treatments, such as knee replacement surgery, which can be expensive and require a lengthy recovery period. Moreover, osteoarthritis is a leading cause of disability, which can impact individuals' ability to work and participate in daily activities, leading to additional economic and social burdens.

Research has shown a strong relationship between knee adduction moment and knee joint osteoarthritis. The knee adduction moment is the force that pushes the knee inward during walking or other weight-bearing activities. Studies have found that individuals with higher knee adduction moments are at greater risk of developing knee osteoarthritis or experiencing disease progression. Moreover, high knee adduction moments have been associated with increased pain and reduced function in individuals with existing knee osteoarthritis. The knee adduction moment has been identified as a reliable and valid indicator of knee osteoarthritis, and it can be estimated using various techniques, such as motion capture and force plate systems. Therefore, monitoring knee adduction moment can be an essential tool for early detection, prevention, and management of knee osteoarthritis.

Using camera systems to estimate knee adduction moments in clinical settings can be challenging due to the need for specialized equipment and controlled laboratory environments. Moreover, traditional motion capture systems may not be practical or feasible for long-term monitoring of knee adduction moments outside of a research setting. To overcome these limitations, wearable sensors have been developed to estimate knee adduction moments in real-world settings. These sensors can be placed on the body and continuously monitor knee joint loading during various activities. Recent studies have shown that wearable sensors can provide reliable estimates of knee adduction moment and can be used to monitor knee joint loading in individuals with knee osteoarthritis. Using wearable sensors to estimate knee adduction moment has the potential to enhance the accuracy and feasibility of assessing knee joint loading outside of the laboratory and in clinical settings.

Recent advancements in machine learning have enabled the development of sophisticated algorithms to estimate knee adduction moments. Long Short-Term Memory (LSTM) models, a type of recurrent neural network, have been shown to be effective in estimating knee adduction moments from wearable sensor data. LSTM models are particularly useful for time series data, such as those collected by wearable sensors, as they can capture the temporal dynamics of knee joint loading during various activities. LSTM models can be trained on large datasets of sensor data to predict knee adduction moment accurately and can be used to monitor knee joint loading in real-time during daily activities. Using LSTM models to estimate knee adduction moment can provide a more objective and accurate assessment of knee joint loading and may be helpful in interventions for individuals with knee osteoarthritis. However, further research is needed to validate the accuracy and reliability of LSTM models for estimating knee adduction moment and to determine their clinical utility in real-world settings.

Purpose

The purpose of this project is to develop and evaluate a Long Short-Term Memory (LSTM) model for predicting knee adduction moments using wearable sensor data. Specifically, we aim to determine the accuracy and reliability of the LSTM model in estimating knee adduction moments during various weight-bearing activities. Additionally, we will examine the stability of the LSTM model by adding noise. By evaluating the performance of the LSTM model, we hope to better understand its potential use in real-world settings for monitoring knee joint loading and informing interventions for individuals with knee osteoarthritis. Ultimately, this experiment may contribute to developing more effective and objective assessments of knee joint loading, potentially improving clinical outcomes for individuals with knee osteoarthritis.

Method

The experiment used a Long Short-Term Memory (LSTM) model from wearable sensor data to predict knee adduction moment (KAM). The input data for the model were time series of sensor data collected from wearable sensors placed on the body of participants during various weight-bearing activities. The ground truth measure of KAM was obtained using a camera-based motion capture system. The LSTM model was constructed using MATLAB software. The model architecture included a single layer of 64 LSTM units with a dropout rate of 0.2, followed by a fully connected layer with a sigmoid activation function. The model was trained using an Adam optimizer with a learning rate of 0.001. The training was performed on a dataset consisting of 80% of the available sensor data, and the remaining 20% was used for testing. The accuracy was assessed using root mean square error (RMSE). The model's stability was assessed by comparing the KAM predictions before and after adding Gaussian noise.

Result

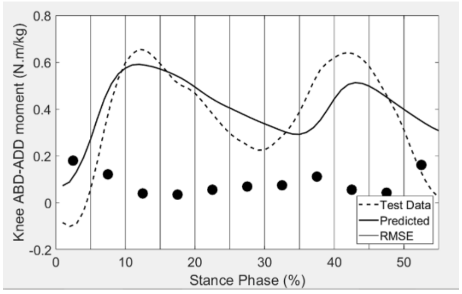
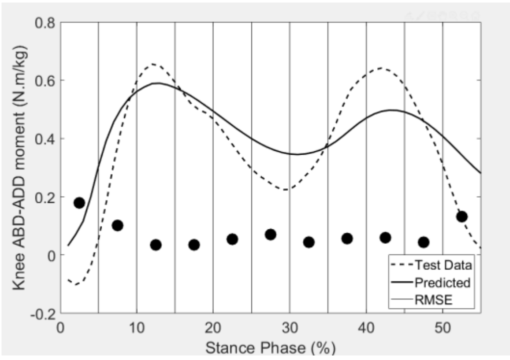
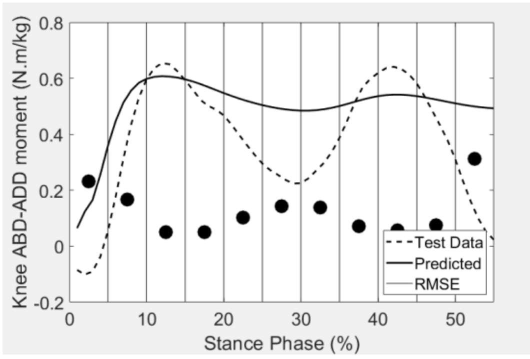


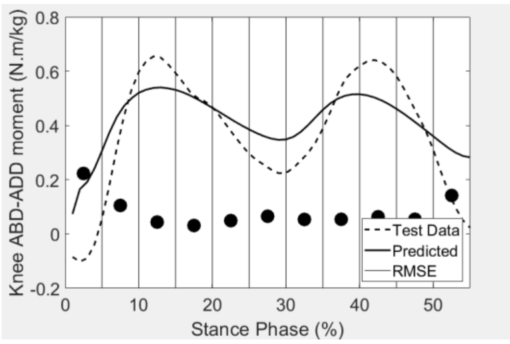
Figure 1. RMSE = 0.1253 before adding Gaussian noise.



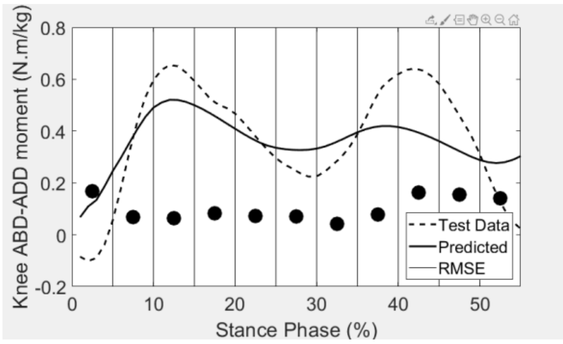
Signal-to-noise ratio (snr) = 100
RMSE = 0.1319



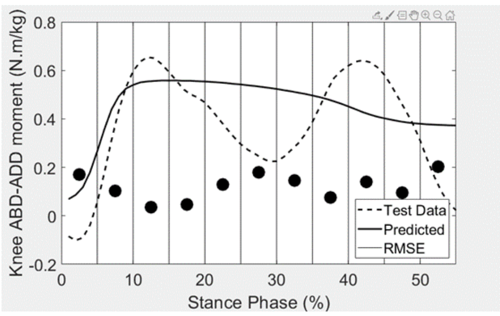
Signal-to-noise ratio (snr) = 75
RMSE = 0.2101



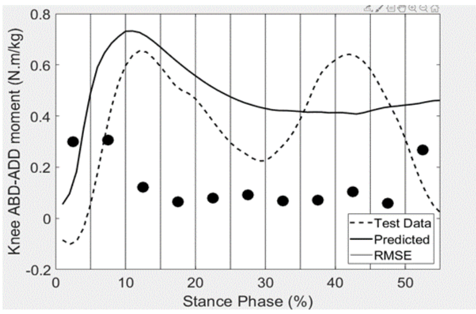
Signal-to-noise ratio (snr) = 50
RMSE = 0.2312



Signal-to-noise ratio (snr) = 25
RMSE = 0. 1405



Signal-to-noise ratio (snr) = 10
RMSE = 0.2027



Signal-to-noise ratio (snr) = 5
RMSE = 0.2673

Figure 2. After adding Gaussian noise under different ***snr*** level

Reference

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