Estimating Ground Reaction Forces from Inertial Measurement Sensor Data

Alexander Beattie[1], **Aku Sinokki**[1], Matti Kortelainen[1], Paavo Vartiainen[1], and Pasi Karjalainen[1]
[1]HUMEA Laboratory, Department of Technical Physics, University of Eastern Finland, Kuopio, Finland
Email: alexander.beattie@uef.fi aku.sinokki@uef.fi

Summary

This work presents a methodology for estimating ground reaction forces from kinematic data. A neural network was developed using data from wearable inertial sensors recorded during gait to estimate ground reaction forces. Ground reaction forces were recorded on a force plate for a single step per trial and the trained network successfully predicted the forces for the other steps. With this information, joint moments within the body can be estimated for gait both inside and outside the laboratory environment.

Introduction

The ground reaction force (GRF) is the force exerted by the ground on a subject's foot. The GRF is required to estimate the forces and moments within different joints of the body. Experimentally measuring GRFs require floor embedded force plates which constrains data collection to well-equipped laboratories.

Previously, GRFs have been estimated with machine learning using muscle activations from EMG signals [1]. Additionally, the GRF is commonly estimated using ground contact simulation which generally assumes that the ground is flat and level. IMUs have also been used to estimate the GRF using forward dynamics simulations coupled with Extended Kalman Filtering [2].

Methods

In this work, participant data from the Kuopio-Gait dataset [3] was utilized to train a neural network and analyze its effectiveness. The dataset consists of gait trials from 51 healthy subjects.

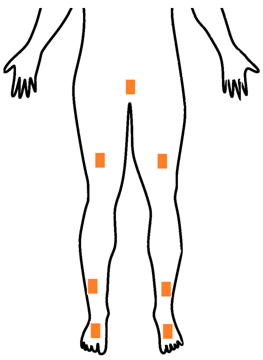

Figure 1: IMU placements [pelvis, thighs, shanks, and calcanei]

Subjects were instructed to walk at three gait speeds, slow, comfortable, and fast while landing one foot on a force plate during each trial to capture a single GRF. Seven wearable inertial measurement units (IMU) were attached to the lower body as described in Figure 1.

A fully connected four layer neural network (NN) was designed for this study. Input data for the NN was sensor orientation (four-element quaternion), and 3D acceleration recordings from each IMU sensor. The output of the network is a three-element vector representing the X, Y, and Z components of the estimated GRF. In the training phase, the GRF was estimated by the NN and compared to the actual GRF recorded by the force plate. The trained network was then used to estimate the GRF for each step of the gait trial.

Results and Discussion

The developed predictor successfully estimated the GRF using previously unseen IMU data.

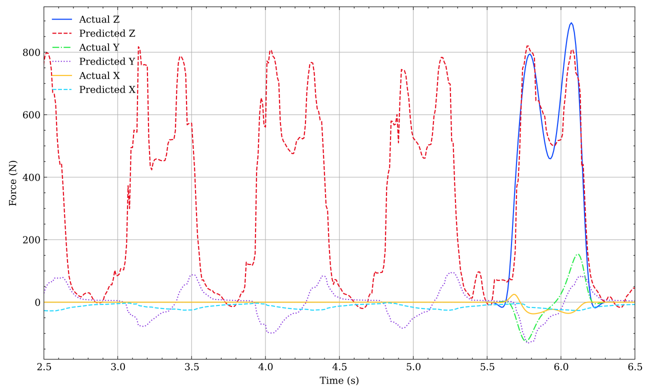

Figure 2: GRF predictions for one trial of comfortable gait walking

The force output in Figure 2 is normalized with respect to all participants in the dataset to create a scale-invariant prediction. The prediction results are then scaled using the subject's mass and the force of gravity to obtain the GRF.

The result is filtered using a low-pass filter with a cut-off frequency of 12 Hz to improve the continuity of the resultant signal. In addition to calculating the GRF, further work is being conducted to add the estimation of the ground reaction moment (GRM) which is the turning effect of the force. Estimating this during each step will enable estimation of ankle, knee, and hip joint moments.

Conclusions

Obtaining GRFs using only wearable IMU data paves the way for improved motion measurement outside of laboratory facilities and will continue to provide advancements in biomechanics by decreasing measurement complexity.

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