Predicting Lower Limb Muscle Strength with Feed Forward Neural Networks

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Introduction: Reducing the total number of sensors in a measurement system can lower the time and cost associated with experimentally measuring human movement. Currently, the number of sensors is strongly influenced by standard practices and application. For example, gait kinematics are measured with various sensors, including passive markers, accelerometers, gyroscopes, and goniometers [1]. Current experimental practices do not always minimize the number of sensors because identifying the minimal set of sensors needed for a given experiment is challenging. Here, we propose a computational method that combines musculoskeletal simulations and machine learning to inform sensor unit reduction. We specifically examine whether a feedforward neural network can accurately classify simulated changes in muscle strength with varying numbers of sensors.

Materials and Methods: To identify the minimum number of sensors required to predict changes in rectus femoris muscle strength, we applied a feedforward neural network to a simulation-based gait dataset. The gait dataset consisted of the joint angles generated from 100 forward dynamic simulations of walking in OpenSim [2]. In each simulation, the size of the simulated person (height and weight) and strength of the right rectus femoris (maximum isometric muscle force) was randomly varied between ±15% of a 50th percentile male (Gait2354 model). A feedforward neural network with a variable input node size, 150 nodes in each hidden layer, and one output node was created using Pytorch. The ReLu6 activation function and a P=0.2 dropout was implemented between the input and hidden layers. The model was optimized with Adamax for 35 epochs and a learning rate of 0.001. To test how the accuracy of the neural network varies with the quantity of input data, the kinematic data in the gait dataset was classified by leg (right, left, both) and joint (hip, knee, and ankle). This created a total of 9 groups. Data from each group was separately inputted into the neural network to classify whether the rectus femoris was stronger or weaker than the 50th percentile male. Accuracies, calculated as the mean and standard deviations from ten iterations of 20-fold cross validation [3], were compared across groups.

Results and Discussion: The feedforward neural network provided insights into a potential approach for effective sensor unit reduction: limit sensors to a single leg and a single joint. When comparing the prediction accuracies across leg groups, the right leg performed within one standard deviation of both legs, while the left leg did not (Fig. 1B). This suggests that halving sensor units by measuring the right leg alone may be sufficient in predicting right rectus femoris strength. Given that only the right leg was perturbed in this study, unilateral measurements may only be justified when studying unilateral perturbations. When comparing the prediction accuracies across joint groups, the hip performed best, followed by the knee, and then the ankle. The right hip, right knee and right ankle contain 9, 2 and 6 joint angle measurements respectively (Fig. 1A). Although there is a 2.27% difference in prediction accuracy between the right hip (87.79%) and right knee (85.52%), it is at the cost of more than 4 times the number of joint angle measurements. Therefore, when considering sensor unit reduction as a high priority, a single joint, the knee, may be sufficient in predicting rectus femoris strength.

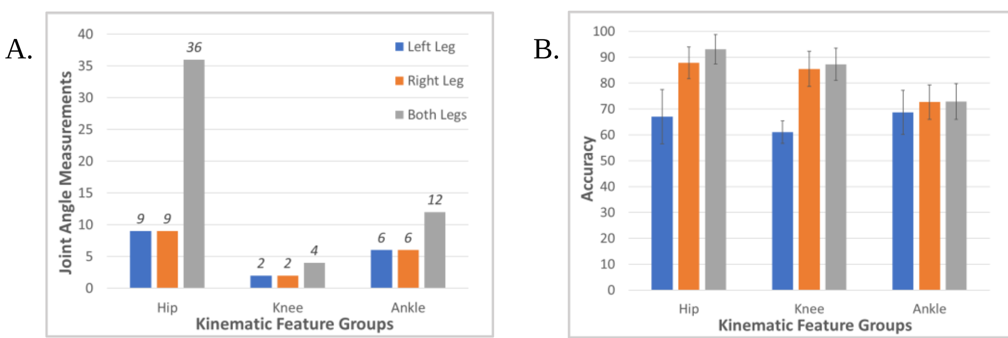

Figure 1. (A) Number of joint angle measurements (above bars) within each kinematic and leg group. (B) Prediction accuracy versus kinematic feature groups compared across leg groups.

Conclusions: This work highlights the potential for machine learning to inform sensor unit reduction in the field of human movement biomechanics. However, given that the dataset is entirely simulated, further study is needed to evaluate how well the results transfer to an experimental setting. Future work could explore scenarios more complex than strength prediction and establish sensor selection standards that optimize price, time, and accuracy.

References: [1] Weijun T. et al. *Sensors* 2012. 12(2): 2255-2283. [2] Delp S. et al. *IEEE Trans Biomed Eng* 2007. 54(11):1940-1950 [3] Refaeilzadeh P. et al. Encycl. Database Syst. 2009.