Electromyograph Estimation of Wheelchair Operations Using Deep Learning

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Introduction: The Paralympic Games have been attracting attention due to the improvement in the competitiveness of sports competitions. Therefore, exercise analysis using myopotential, performance evaluation, and condition evaluation, among others, are being actively promoted to improve competitiveness. However, because of the limitations of physical actions and the discomfort associated with attaching electrodes, devices, and cables to the body, EMG is often used under controlled conditions [1]. As a result, in this study, we developed a method for estimating myoelectric potential with a neural network using a video camera and an inertial sensor that can be used in a real-world competition setting.

Methods: While the wheelchair was in operation, we collected synchronous data from cameras, inertial sensors, and EMG. Three healthy male university students served as participants. Three cameras (Pocket Cinema Camera 4K, Blackmagic Design Pty. Ltd.) were used and were strategically placed to capture images of the entire measurement field (10×10 m^2). The recording was conducted at a sampling frequency of 60 Hz and a resolution of 4K. In addition, inertia sensors (IMS-SD, Tec Gihan Co., Ltd.) were installed under the wheelchair and in the center of both wheels. The sampling frequency was 1,000 Hz. The resolution of the acceleration sensors was set to 12 bits and the dynamic range to ±16 G. The angular velocity sensor had a resolution of 16 bits and a dynamic range of ±2,000 dps. EMG (Polymate Pro MP6000, Miyuki Giken Co., Ltd.) was used for obtaining the ground truth data and myopotential measurement points were flexor digitorum profundus on the right hand, biceps brachii, triceps brachii muscle, rear deltoid, and right pectoralis major. The sampling frequency was 1,000 Hz. As full-wave rectification smoothing processing, the absolute value of the amplitude was sought, and a low-pass filter with a cutoff frequency of 2.6 Hz was employed [2]. We then normalized the maximum myopotential for the myopotential data for each test participant, %MVC. The target movement was forward at four intensities: zigzag, 90° turn, and 180° turn. Figure 1 shows the architecture of the designed model. The input data were the 3D coordinates of the 16 joints of the body calculated from the camera images and the 3D acceleration data of the wheelchair. The output

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values were set to various myopotential data. The formed dataset has a total of 4,502 data. The designed model was trained using data for each muscle within each test participant, with training and evaluation data randomly split in a ratio of 8:2. When learning, the Adam optimization function was used, the learning ratio was 0.01, and the number of learning times was 30000.

Results: The learned model was applied to the evaluation data to verify the accuracy of the myopotential estimation. Fig 2 shows the correlation coefficient between the estimated and true values for each of the participants.

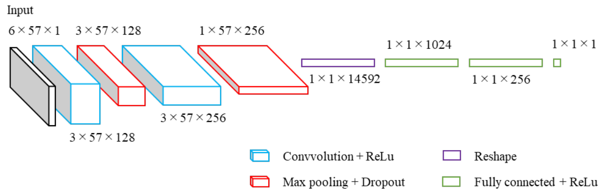

Fig. 1: Architecture of the designed model (not to scale)

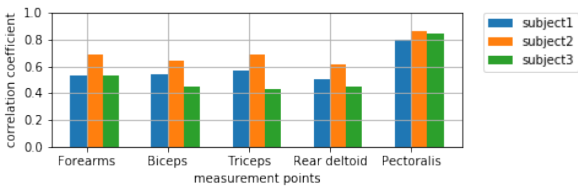

Fig. 2: Correlation coefficient between measured myopotential values and proposed model estimated values

Conclusion: In this study, using a camera image and an inertial sensor attached to a wheelchair, we proposed a simple method for measuring myoelectric potential using a convolutional neural network. We achieved the same level of estimation accuracy as previous studies [3] that estimate myopotentials during dynamic load tasks by solving inverse dynamics and optimization problems with optical motion capture and electromagnetic tracker measurements as inputs. The study was conducted according to the guidelines of the Declaration of Helsinki, and approved by the Ethics Committee of Nagaoka University of Technology (protocol code :2017-38).

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