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論 文 要 旨

THESIS SUMMARY

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要旨（英文 800 語程度）
Thesis Summary (approx.800 English Words)

The existing Electromyography (EMG) interfaces usually cover two different applications. One is a discrete classification of complex motions, and the other is a regression of a single joint. However, the complex regression model is elusive because of the crosstalk inherent in EMG signals. Surface EMGs inevitably capture the target and adjacent muscle activities with several noises. Therefore, this study conducts signal source derivation and analyzes the complex hand motion from the signal sources. I identify the signal source of EMG with muscle synergy because muscle synergy is defined as a group of muscle activation from the neural commands. The muscle synergy implements two separation algorithms. One is non-negative matrix factorization (NMF), and the other is independent component analysis (ICA). This study utilizes the synergy algorithms to separate signal sources or muscles before estimation models to confirm the remaining movement information.

The first experiment implemented muscle synergy on signal source separation from the complex hand movements maintaining the crucial information. Participants are asked to conduct two-dimensional wrist movements (flexion/extension and radial/ulnar deviation) and gripping. Based on the anatomy, five muscles for wrist movements and two muscles for gripping located in the forearm are measured together with wrist angle and grip force references. Linear envelop converts EMG signals to quasi-tension, highly correlated parameters to the joint torque, and NMF is applied on the normalized quasi-tensions per movement type. Muscle synergy is calculated per movement type with more than 0.9 variance account basis. Then linear regression processes wrist motion estimation using muscle synergies. The regression evaluators are correlation coefficients with normalized root mean squared error. Muscle synergy-based regression gets compared with the musculoskeletal model that estimates wrist angles using individual quasi-tension. When all wrist movements with and without gripping are considered, muscle synergy-based regression showed better estimation performance than the musculoskeletal model having higher correlation coefficients (0.789±0.084) and lower error (0.156±0.038). Muscle synergy also showed high correlation coefficients in gripping force estimation (0.846±0.050). However, gripping also showed the limit of muscle synergy-based regression showing the collapse of wrist movement estimations when the participant put the gripping force at their maximum force level. The signal source separation is not applicable in full-powered gripping.

The first experiment estimated complex movements that are easy to figure out individually but difficult to separate when performed simultaneously. Unlike the previous one, the next analysis implements finger movement estimation aiming at dexterous hand motion estimation. It requires the identification of deep muscle activities, hard to detect in the surface EMGs. Therefore, the number of EMGs increases up to ninety-six channels in a high-density EMGs manner. The sensors spread over the upper limb. The participants perform touchpad control, one-step index finger motion in eight directions in two different fixed elbow postures (0 and 90-degree elbow flexion). The muscle signals used at this time are discriminated by muscle synergy. Some high-density EMGs contain merely noise components because they are spaced in the area. Therefore, ICA is applied to the sensor signals then task-irrelevant independent components are excluded. The selective ICA passes the linear envelope and performs NMF computation. The resultant muscle synergy becomes the input of the estimation model. It is undesirable to predefine the relationship between the to-be-measured muscle signals and finger movements; Hence I used a convolutional network (CNN), one of the nonlinear estimation methods, giving four different inputs (with and without NMF and ICA) for synergy algorithm comprehension. The estimation performance from CNN showed the highest performance when using only ICA followed by statistically equivalent performance using ICA and NMF. CNN estimation performance drastically increases after the ICA algorithm is applied. And after NMF, the number of input dimensions decreased without the loss of estimation performance. Such results show the role of ICA and NMF that ICA performs in separating noise of high-density EMGs while NMF performs in a reduction of input dimensions. The comparison between similar input-types based on channel activation specifies what algorithms do. NMF combines co-activating EMG region without noise elimination, and ICA increases the fidelity of deep muscle activities to a similar extent to superficial muscle activities.

Through two experiments, muscle synergy showed the feasibility of signal source derivation and deep muscle identification. It also showed that such separations maintain crucial information for estimation models such as linear regression and CNN. However, it also brought about several considerations and problems. Complex hand motion estimation showed the possibility that signal sources might change or break the rule on exerting action. Besides, deep muscle identification demands more strict constraints of non-target movements. The discrimination could capture all the activating muscle activities. It might require consideration of all joint motion related to muscles within the sensor region.