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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 ）

Brain activity decoding aims to disclose and predict the intention or mental status inherent in the biological brain by the utilization of brain recording signals. To accomplish the feature extraction and pattern recognition for the pre-processed brain recording signal, the machine learning methods have been widely utilized for the brain activity decoding tasks. However, the existing methods of brain activity measurement, such as electroencephalogram (EEG), electrocorticography (ECoG), as well as the functional magnetic resonance imaging (fMRI), are considerably prone to the interference of physiological artifacts or other environmental noises, which are usually intractable for the conventional machine learning algorithms, thus leading to unsatisfactory brain decoding performance.

To address this issue, the present thesis aims to propose new robust brain activity decoding algorithms which are expected to achieve adequate decoding performance even though the brain signals are considerably contaminated by miscellaneous noises. The main motivation of this thesis is the information theoretic learning (ITL) framework, which refers to adopting the information-theory-based descriptors to formulate the objective functions for machine learning models. In particular, two popular learning criteria, namely minimum error entropy criterion (MEE) and maximum correntropy criterion (MCC), were employed in this thesis to propose robust brain decoding algorithms to improve the decoding performance for real-world noisy brain recordings, motivated by the exceptional robustness of these two learning criteria. To be specific, MEE is proper for the condition of multi-peak error distribution while MCC can deal with outliers very well.

First, this thesis investigated the noisy classification task. It was found that the optimal error distribution for the noisy classification scenario exhibits a three-peak distribution, for which the original MEE or the quantized MEE (QMEE) is supposed to reveal satisfactory robustness because they are in particular proper to deal with a multi-peak distributed error distribution. However, they showed unexpected instability for a noisy classification task. By investigating the reason, this thesis proposed a new learning criterion for robust classification which aims at maximizing the inner-product similarity measure between the current error distribution and the optimal three-peak case, which is exactly a special case for QMEE with a restricted codebook, thus named it as RMEE. For the proposed RMEE, the discussions for optimization and convergence analysis are given. In the performance evaluation, first RMEE based logistic regression shows better robustness in the synthetic dataset than conventional cross entropy (CE) and also outperforms MCC. For the noisy EEG datasets, RMEE based extreme learning machine (ELM) model achieves the highest accuracy in most cases. In addition, RMEE based ELM realizes promising performance in other benchmark datasets as well.

Then, this thesis also takes another issue for brain activity decoding into account, the high-dimensional problem, which means that the number of covariates is larger than that of the

training samples and will usually lead to serious over-fitting or ill-posed solutions. This issue mainly arises from the difficulty to collect a large number of brain activity trials, in contrast to the excellent spatial resolution of fMRI and high temporal resolution of EEG/ECoG. There are mainly two popular strategies to solve the high-dimensional problem, i.e. dimensionality reduction and feature selection. This thesis further investigated the integration of robust ITL method with these two strategies to solve the noise-robust and high-dimensional problems simultaneously.

For the noisy and high-dimensional scenario, this thesis investigated a robust version for the dimensionality reduction based decoding algorithm, partial least square regression (PLSR), which projects both input and output by maximizing their covariance after dimensionality reduction and then builds the regression relationship, and is popular for ECoG decoding task. This thesis proposed a robust variant for the PLSR algorithm by reformulating the non-robust second-order statistics by the MCC framework. The proposed partial maximum correntropy regression (PMCR) algorithm learns robust projectors for input and output simultaneously and acquires each model parameter with MCC. The experimental results with the synthetic toy and Neurotycho ECoG dataset demonstrate that the proposed PMCR could outperform the existing PLSR algorithms, revealing promising robustness for high-dimensional and noisy ECoG decoding.

Further, this thesis discussed the integration of MCC with the feature selection strategy to realize robust and sparse brain decoding. To be specific, MCC was integrated with the sparse Bayesian learning method with the automatic relevance determination (ARD) technique for adaptive sparseness that automatically tunes the feature selection. Based on this proposal, a correntropy-based sparse logistic regression (CSLR) algorithm was proposed for robust and sparse classification. The proposed CSLR algorithm was evaluated on various noisy and high-dimensional classification scenarios, including a synthetic example, the EEG decoding task, and the fMRI-based visual decoding task. Experimental results demonstrate that CSLR can realize better classification accuracy and feature selection in the brain activity decoding task. Furthermore, this thesis investigated the inherent noise assumption under the MCC-based regression and derived an explicit MCC-aware noise distribution. By utilizing the MCC-aware likelihood function and the ARD technique, the MCC-based robust regression could be also implemented with adaptive sparseness. The proposed MCC-ARD algorithm for robust sparse regression can realize superior regression performance and feature selection in a noisy and high-dimensional scenario than existing methods.

In summary, ITL can alleviate the performance deterioration resulting from the complicated brain recording noises for the real-world brain activity decoding tasks, thus promoting the investigation of brain mechanism as well as the development of brain-computer interface.