学位論文題目

Unlearned class estimation based on complementary event model and its application to biological signal classification

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Computational automation systems based on machine learning have seen significant development in recent years, with examples including image recognition technology, man-machine interfaces, and temporal data models for stock price prediction. In the fields of welfare and medicine, effectiveness in pattern recognition technology has also been reported for anomaly detection in medical imagery and the development of myoelectric prosthetic hands.

Classifiers in general simply identify classes predefined in training, but cannot be applied to consideration of specific undefined classes with abnormal patterns. If unknown patterns belonging to undefined classes are input into a trained classifier, misclassification relating to predefined classes will inevitably result. This can cause misclassification of unknown diseases in diagnosis assistance and critical errors in interface control. To address this, unlearned patterns not included in training data need to be recognized.

A variety of classifiers are used to detect unexpected outliers during training. The authors also performed research to enable highly accurate anomaly detection with the novel stochastic OVRGMN (One-vs.-Rest Gaussian Mixture Network) approach, with definition and application of complementary Gaussian distribution. The main issues of previous methods involve the difficulty of stable optimization with small pools of learning data and appropriate thresholds, along with the challenges involved in setting appropriate empirical thresholds. The OVRGMN is also premised on application of the static characteristics of input data, and cannot be used to handle time-series data.

This research was performed to develop novel unlearned class detection superior to previous methods and support classification and evaluation of biological signals.

The Normal and Complementary Gaussian Mixture Network (NACGMN) was applied as a novel probabilistic neural approach with unlearned class detection for high classification performance and stable training even with small training samples. The NACGMN incorporates Gaussian mixture models (GMMs) and complementary Gaussian mixture models (CGMMs) representing distribution of training and unlearned classes, respectively. Since the parameters of both distributions can be determined as weighting coefficients of the network with relaxed statistical constraints, the NACGMN supports more stable training. The outcomes of classification experiments employing artificial data and EMG signals demonstrated the validity of the NACGMN.

To extend the proposed network to a classifier capable of handling time-series information, novel

One-vs.-Rest hidden Markov Model (OVRHMM) classification was proposed in which time-series data for trained classes are modeled using hidden Markov models (HMMs) with GMMs and unlearned patterns are expressed using HMMs with CGMMs. Based on *a posterior* probabilities estimated using Bayes' theorem, the OVRHMM can be used to stochastically evaluate the degree of abnormality for input signals. Experimental results indicated that the ORVHMM enabled classification of time-series data that cannot be discriminated using static classifiers.

A time-series data classification model based on the Hidden Semi-Markov Model (HSMM), in which an anomaly state with the CGMM is introduced, was also proposed for more detailed anomaly detection. The related novel classification method combining Bayesian discrimination in consideration of temporal information and estimation of state transition sequencing supports highly accurate classification and detailed anomaly detection. To evaluate the effectiveness of the proposed HSMM for real data, the approach was applied to the classification of care-worker motion with outcomes demonstrating accurate detection and recognition of important work among innumerable movements.

The above achievements show that unlearned-class detection based on complementary event models enabled stable training independent of learning conditions and high-precision classification in consideration of time-series data.