学　位　論　文　内　容　の　要　旨

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学　位　論　文　題　名

A Robust Self-Constructing Normalized Gaussian Network for Online Machine Learning
（オンライン機械学習のための頑健な自己構築正規化ガウスネットワーク）

In this thesis, we aim to improve the robustness and applicability of Normalized Gaussian networks (NGnet) in the context of online machine learning tasks.

A challenging problem in online machine learning is the limited domain knowledge provoked by restricted prior knowledge and receiving additional information only sequentially over time. Also, when received data are not identically and independently distributed in the input space, artificial neural networks (ANN) tend to be prone to negative interference. These limitations make the application of ANNs to online learning tasks difficult, since fine-tuning before training is not possible in the absence of prior-knowledge and readily available big batches of data samples. It is then necessary to apply learning methods that are able to act robustly in those environments over a wide range of learning parameters without major fine tuning. Another challenge for online ANN training is the selection of an accurate model complexity that is able to represent the underlying learning problem well without over- or under-fitting. When domain knowledge is limited, a common approach is to select the model complexity dynamically during learning by increasing or decreasing the complexity according to the sequentially received training data samples.

In this thesis, we consider the problem of robustness in online learning tasks for the NGnet. The NGnet belongs to a group of ANNs that possess local properties due to their receptive field based network architectures. These local architectural properties make it a good candidate to deal with negative interference prone environments. For further improvement of robustness and ease of application of the NGnet in online learning tasks, we revise a previously proposed localized forgetting approach for the NGnet and adapt dynamic model complexity selection to it. The localized forgetting approach helps to improve the robustness against negative interference compared to an earlier training approach for the NGnet with global forgetting. Yet, in its originally proposed derivation it is not applicable over the whole numerical range of a forgetting factor. Therefore, we revise the derivation by considering an additional dependency on time resulting in a localized forgetting approach that is applicable over the whole numerical range of the forgetting factor. Also, while dynamic model selection has been considered for an earlier training approach of the NGnet with global forgetting, it was yet considered for the NGnet with localized forgetting and only static model selection was possible. So, we apply dynamic model selection to it for the first time in a self-constructing approach, where prior to training no network units have to be initialized and it becomes easier to deal with the limited domain knowledge. In addition, the model selection mechanisms are improved to achieve better robustness in negative interference prone environments, and a new merge manipulation is considered to deal with model redundancies.

The effectiveness of the proposed method is compared with the previous localized forgetting approach and an established learning method for the NGnet with global forgetting. Several experiments are conducted for a function approximation task to evaluate the overall and partial performance of the improvements compared to the earlier approaches. Also, chaotic time series forecasting and reinforcement learning tasks are tested to evaluate the overall performance for difficult learning tasks.
The improved method possesses robust and favorable performance in different learning situations over all testbeds, making it an interesting alternative to the earlier approaches for online learning environments with proneness to negative interference.