Evolving Takagi-Sugeno Fuzzy Models for Data Mining

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Abstract - We are studying and experiencing approaches for adaptive on-line learning of fuzzy rules and their application for prediction problems in the context of data mining. Takagi-Sugeno (TS) fuzzy models are used for knowledge representation and the mechanism for on-line learning is based on algorithms that recursively update the model structure and parameters by combining supervised and unsupervised (hybrid) learning. The structure and parameters of the model continually evolve by adding new rules and by modifying existing rules and parameters during the operation of the system. The work is based on developments from the original contributions of Stephen Chiu, Plamen Angelov and Nikola Kasabov.

Key words: Takagi-Sugeno fuzzy models, fuzzy clustering, rule-base adaptation, on-line learning.

1. Evolving Takagi-Sugeno Fuzzy Models

Takagi-Sugeno fuzzy models have recently become a powerful practical engineering tool for modelling of complex systems. Evolving rule-based models use methods for learning models from data are based on the idea of consecutive structure and parameter identification. Structure identification includes estimation of the focal points of the rules (antecedent parameters) by fuzzy clustering. With fixed antecedent parameters, the TS fuzzy model transforms into a linear model. Parameters of the linear models associated with each of the rule antecedents are obtained by applying the recursive least-squares (RLS) method or the weighted recursive least-squares (wRLS) method.

For on-line learning of the TS fuzzy models it is necessary an on-line clustering method responsible for the model structure learning. Angelov proposed a new method inspired on the subtractive clustering algorithm that allows the recursive calculation of the informative potential of the data, which represents a spatial proximity measure used to define the focal points of the rules. Evolving rule based models use the information potential of the new data sample as a trigger to update the rule base.

The evolution mechanism is basically the following: If the information potential of the new data sample is higher than the potential of the existing rules a new focal point (rule) is created. If the new focal point is too close to a previously existing rule then the old rule is replaced by the new one. The advantage of using the information potential instead of the distance to a certain rule centre only for forming the rule base is that the spatial information and history are not ignored, but are part of the decision whether to upgrade or modify the rule base.

The recursive procedure for on-line learning of evolving TS fuzzy models includes the following stages:

Stage 1: Initialization of the rule-base structure (antecedent part of the rules);

Stage 2: Reading the next data sample;

Stage 3: Recursive calculation of the potential of each new data sample;

Stage 4: Recursive up-date of the potentials of old centres taking into account the influence of the new data sample;

Stage 5: Possible modification or up-grade of the rule-base structure based on the potential of the new data sample in comparison to the potential of the existing rules centres;

Stage 6: Recursive calculation of the consequence parameters;

Stage 7: Prediction of the output for the next time step.

Despite of the merits the algorithm still needs some major improvements. The conditions to modify and upgrade the fuzzy rules are being studied more deeply since they influence the number of created and modified rules and it is not easy to adjust the definitions for a specific problem.

Another vital issue is the on-line clustering procedure, particularly the function for recursive calculation of the potential of each new data sample. Angelov used different functions (Cauchy type function of first order, exponential with the summation in the exponent) for recursive calculation of the potential but all present limitations because the local maxima of the potential do not cover all the regions of interest. New functions or estimators from information theory need to be tested to achieve a better placement for focal points covering not only the regions of higher density of points but also other regions of interest (a disturbance or a new operating mode).

2. Experimental Results

The approaches and its developments were tested on a benchmark problem, the Mackey-Glass chaotic time series prediction. The data set has been used as a benchmark example in areas of fuzzy systems, neural networks and hybrid systems. Several models were built for different parameters of the algorithm and particularly for the conditions necessary to create and modify the fuzzy rules. The results obtained were compared with other methods (ESOM, EFuNN and DENFIS) and one of the conclusions is that it is possible to obtain identical values for NDEI with a lower number of rules, i.e. more transparent models.

There are a few parameters (radii, Omega for (w)RLS) and conditions that need to be specified, which give the flexibility to tune the search. There are several possibilities for the definitions to create and modify fuzzy rules and different models will be obtained. It is quite difficult to define one condition that is the best for all types of problems.

3. Conclusion

The approaches we are studying and experimenting for on-line identification of evolving Takagi-Sugeno fuzzy models are computationally effective and despite the necessary improvements the adaptive nature of these models, in combination with the highly transparent and compact form of fuzzy rules, makes them a useful tool for on-line modelling.

References

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