Epilog – Achievements, Open Problems and New Challenges in EFS

This book deals with many aspects in the field of evolving fuzzy systems which have emerged rapidly during the last decade and meanwhile have become well established in the fuzzy community. The establishment is underlined by a huge amount of publications in international fuzzy conferences and journals (such as Fuzzy Sets and Systems (Elsevier), IEEE Transactions on Fuzzy Systems (IEEE Press), IEEE Transactions on Systems, Man and Cybernetics part B (IEEE Press), Information Sciences (Elsevier), International Journal of Approximate Reasoning (Elsevier), Applied Soft Computing (Elsevier), Evolving Systems (Springer) and others) and by the organization of several special sessions and workshops during the recent years at international fuzzy conferences and symposia. This book covers not only a comprehensive survey of the most important evolving modelling approaches and the most important incremental learning algorithms they contain, but also presenting significant extensions for guiding evolving fuzzy systems to higher process safety, predictive quality, user-friendliness and interpretability as well as understandability of its components and finally the processes which they are modelling. Applications from different industrial fields including multi-channel measurement systems (identification, prediction and plausibility analysis), visual and audio inspection tasks, psychological aspects in texture analysis, applications in bio-informatics, eSensors or financial market forecasting should underline the necessity, applicability and reliability of evolving fuzzy systems in these fields. Therefore, and as the evolving concepts presented in this book allow the machines to permanently learn from changing environments and enrich their knowledge, the book may serve as another cornerstone for a step towards computational intelligence. Even though, based on all these facets, the reader may get a nice impression about the range of applicability and the methodological richness of evolving fuzzy systems, there are still some open problems in EFS which have not been handled with sufficient care and necessary detail so far (although discussed in some sections in this book): [1]

- **Avoidance of over-fitting**: currently most of the evolving fuzzy system approaches use the least squares error optimization problem for optimizing linear parameters (mostly in rule consequent functions of TS-type fuzzy systems): this leads to a recursive least squares (in case of global learning) or recursive fuzzily weighted least squares (in case of local learning) algorithms, which may over-fit significantly on the (permanently loaded) training data. This is because, the model complexity is not included in the formulation of the optimization problem; contrary in an off-line setting, the learning based on least squares error often is performed through N-fold cross-validation which can resolve the problem of over-fitting by eliciting error on separate test samples (folds) — see also Section 2.8 for a more extensive discussion on this topic. In fact, an appropriate rule merging approach as discussed in Section 5.1 may overcome some deficiencies in this regard, however this denotes a more heuristic approach rather than relying on analytical incremental optimization procedures with a more theoretic basis.
- **Fault handling**: although there exist some concepts (rule base procrastination, incremental quantiles [428], recursive potentials) for dealing with (unique, couple of) outliers in various EFS approaches, currently, there exists no enhanced concept for dealing with systematic faults, appearing in new regions of the feature space; in fact, the distinction to the appearance of new system states or operating conditions also extending the feature space has not been studied so far.
- **Drift handling**: although we presented a concept for the automatic detection and treatment of drifts and shifts in data streams in Section 4.2, this is only a first attempt in this direction, especially designed for *FLEXFIS* and *eTS* and this in a quite heuristic fashion, and therefore far from being fully investigated. In this regard, also the concept of multi-task learning [68] in connection with EFS has not been studied so far.
- **On-line curse of dimensionality reduction**: Section 5.2 indeed demonstrates a reasonable concept for a soft dimension reduction in in EFS by using feature weights whose values are changed slightly with new incoming samples, therefore discontinuities in the learning process (as would be forced by crisp on-line feature selection) can be avoided. However, this approach is far from being optimal, as the feature weighting is performed by a linear filter approach and as such not related/embedded with the underlying fuzzy model architecture. Indeed, important features in a linear sense are also important ones for non-linear fuzzy models, but some other unimportant features may turn out to be important when

[1] At this point, the author wants to emphasize that this book covers all approaches, methods and algorithms which were published before 30th of June 2010 as crisp deadline; the author apologizes for eventually overlooking some important novel concepts and aspects which were published before this date and also for not being able (due to time restrictions) to take into account any novel concepts and aspects published after this date — in both cases the author of this book would be grateful and invites the reader for any valuable comments, critics, claims, suggestions for improvement.

inspected through a non-linear approach (ideally coupled with the fuzzy model architecture as embedded approach).

- **Extrapolation problematic**: it is not fully understood how the left and right most fuzzy sets in fuzzy partitions should be optimally extended in the extrapolation region in order to give reliable predictions and classification statements; first attempts are presented in Section 4.6, especially dealing with the avoidance of re-activating inner membership functions with infinite support.

New challenges for EFS include the following aspects:

- **Active learning scenarios**: So far, the assumption in most of the EFS approaches is that the response data (labels, target values) are provided together with the input feature/variable vectors and incremental training and evolution of the models continues in a life-long learning mode. However, the concept of active learning in connection with EFS has not been sufficiently studied so far (a first attempt is presented in Section 5.3): active learning may be very important in order to decrease the annotation effort and response times of operators during on-line mode, especially for classification problems, as active learning makes explicit selection of important samples possible which may help the models to improve their qualities, and synchronously neglecting unimportant samples. This makes the application of evolving models and especially evolving fuzzy systems much more attractive.
- **Linguistic and visual interpretability**: A large part of Chapter 6 deals with aspects of complexity reduction in EFS, which can be performed in a fast on-line matter; this is far from providing interpretable and for operators, users, experts understandable EFS, only some first ideas in this direction are provided in Chapter 6. Basically, we can say that all the current EFS approaches are precise modelling approaches neglecting completely the interpretable aspect of fuzzy systems, even though including some aspects regarding deletion of obsolete rules or rule merging processes. An exception is a recent publication [180], where more interpretability is achieved by applying a kind of mixed Mamdani and Takagi-Sugeno type model architecture in order to gain more interpretability while still preserving the good approximation accuracy of TS fuzzy models. Visualization aspects and visual interpretation of (high-dimensional) EFS are completely missing in literature, but could be very important for the operators to get a better understanding of what is going on in the on-line processes of the their systems, respectively motivating the users for an enriched human-machine interaction and communication, see subsequent point.
- **Enhanced human-machine interaction**: Combining aspects of active learning with EFS and interpretable and understandable EFS together in an enriched user-interaction concepts, can be one of the key aspects in the near future such that the models benefit from both parties, data samples on the one hand and expert knowledge on the other hand in an alternating exchanging context, leading to the concept of *human-inspired evolving machine/models/fuzzy systems* (see also Section 10.2.3).

- **Dynamic data mining**: the application of EFS approaches was so far mainly concentrated on temporally changing environments. Evolving fuzzy systems have not as yet been applied in a dynamic data mining context (see also Section 5.5.1), where spatially distributed data is used for knowledge exchange via dynamic models.
- **Transfer learning**: transfer learning addresses a similar learning problem as dynamic data mining, where already trained models are updated based on samples loaded from a new data source. The difference to dynamic data mining is basically that models are adjusted to new test objects, devices or environments in order to include the new information — this can also stem from temporal changes and is not necessarily triggered by spatially distributed data sources. Data samples may be given different weights for different devices, objects etc.
- **Combination of EFS with other machine learning techniques**: currently, EFS have hardly been studied in the context of incremental learning in combination with other machine learning methods. We see this as an important and useful future challenge, as both parties, the (evolving) fuzzy systems as well as the machine learning community may benefit from such an exchange w.r.t. learning aspects, model components or parameter adaptation and tuning, enriching the diversity of data-driven methodologies in today's real-world systems.

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