A Survey on Evolving Neuro-Fuzzy Approaches

Keshav Dhir

School of Computer Science and Engineering
Lovely Professional University, Punjab, India

Abstract—Most of the modern availability of dataset consists of assumptions in machine learning and computational intelligence that result in handling online operations to some extent. Emerging as a framework to address the issues of high amount of data increment which makes it very difficult to process if it efficiently using iterative algorithms requiring multiple passes. By properly addressing the issues using single-pass learning, self-adaption and evolving contraction model components on demand and on-fly. This survey focuses on real time environments consisting of all models relating to fuzzy and neuro-fuzzy evolving techniques by performing learning and model development incrementally.

Keywords- Evolving system, adaptive system, fuzzy system

1. Introduction

This paper gives a systematic survey on developed systems, focusing on (neuro) fuzzy systems in clustering, regression, detection and classification. Its purpose is to provide an overview of (neuro-) fuzzy systems leading ideas and concepts about the types of architecture and their main structural components, as well as basic incremental learning algorithms related to addressing parameter optimization and structural development. A variety of developed systems can be seen in Fig.1, which allow the reader to develop the necessary literature, main methodology and design principles to develop modern based applications using principles of more robust and real-life world scenarios in fuzzy based systems.

Various self-learning evolving systems have been studied in engineering, predominantly in the field of adaptive control and system credentials since the early forties [1–3]. The adaptive term usage is based on scheme based techniques that apply where the system model is known partially and not the actual scenario is known. Techniques are dependent on assuming various parameter adjusting [4], employing finite set of local methods with controllers having high level of switching supervisory [5], and most importantly techniques based on iterative learning mechanism [6]. Most of the techniques are based on estimation of parameters of data-driven and self-tuning algorithms.
The systems related to evolving mechanism can be traced back to the year of 1991 with this paper [7], where the new scheme of resource allocation network or in short RAN was introduced for the first time. To summarize the various adaptive control systems and parameter estimation, as well as evolutionary model based algorithms, they helped in developing inheritance and benefit from various knowledge based from learning of data streams [8].

2. Types of Evolving Systems

Developed over for many high end clustering and regression as well as classification domains, various data stream algorithms are used in frequent pattern matching, finance in hard real time scenarios, control of autonomous vehicles and diagnostics in several fields of intelligence [10].

2.1 Evolving systems in identification, clustering and regression

Evolving systems, similarly as adaptive neuro-fuzzy systems, learn from data streams by using learning algorithms to adapt their parameters in an online manner. The parameters in this case are subdivided into linear and nonlinear ones. The nonlinear parameters, such as centers of clusters, width of radial basis functions, (inverse) covariance matrices or information granules, to mention a few, are related to the partition of the input-output space, whereas the linear parameters refer to the parameters of locally valid affine models. The partition of the input-output space is usually done by using different modifications (fuzzy) clustering methods, which are adapted for online usage from their off-line counterparts. These methods are unsupervised and aim at granulating the input-output space to achieve best possible representations of data streams (according to distance- and density-based criteria). The eTS method, for example, uses recursive clustering with subtraction (subtractive clustering).

Evolving methods can also be distinguished regarding the ability of adaptation. Notice that some fuzzy and neuro-fuzzy methods need the initial structure of the model (for example: GANFIS, ANFIS), which is obtained by off-line clustering. In this case, the number of fuzzy rules is constant during online operation and therefore the methods are not considered evolving methods, but adaptive methods since only parameter adaptation is performed online. The first methods to change the structure of the model were called incremental methods. These methods are equipped with mechanisms to add new local models or rules on demand, however they do not have mechanisms to delete old, useless or inactive rules.

2.2 Evolving systems in types of classification

This new type of data and emerging needs are related to kinds of classifiers called incremental, which may update their parameters with new data samples. The development of incremental learning systems that can be trained over time from a data stream is a major open problem in the data mining area. An incremental classifier receives and integrates new examples without the need to perform a full re-learning phase from scratch.

A systematic framework for data analytics is proposed in [11]. The underlying classifier is based on the typicality and eccentricity of the data, and is called TEDAClass (Typically and Eccentricity based Data Analytics Classifier). This classifier is evolving, fully recursive, spatially-aware, non-frequentist and non-
parametric. TEDAClass is based on the TEDA method [12]. It uses local typicality and eccentricity to calculate the closeness between data and fuzzy rules.

In general, the cluster identification algorithms and approaches mentioned in this section should be flexible to changes in the data stream. The number of clusters, cluster sizes and associated parameters should ideally be significantly changing whenever demanded, while still assuring approximative convergence of the model to the (hypothetical) batch solution (achieved when seeing all data samples at once), especially during regular modes in the stream process. Therefore, the stability-plasticity dilemma [13] should be somehow appropriately addressed within any incremental learning method and evolving framework.

3. Literature Survey
The survey of various papers is shown in Table 1 in which year wise development of the evolving systems is mentioned and based on which various applications were established.

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<th>Sr.no</th>
<th>Year</th>
<th>Authors</th>
<th>Topic</th>
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4. Conclusion

Missing data are common in real-world applications. They arise due to incomplete observations, transfer problems, malfunctioning sensors, or incomplete information from experts or public surveys. The missing data problem is still an open topic in non-stationary data stream environments, despite being extensively investigated in off-line settings. Particular sequences of missing data can lead to instability of stable closed-loop control systems and loss of memory in developing fuzzy and neuro-fuzzy modeling. Further issues that are worryingly addressed in the literature include characterization, design of experimental setups, and development, performance evaluation, testing, validation, and the creation of workflows to compare algorithms in non-stationary environments.

The survey discussed various developmental mechanisms on developing intelligent systems for regression and classification with emphasis on fuzzy and neuro-fuzzy methods. An in-depth analysis of the research contributions, especially over the last 15 years, which are fundamental to the current state-of-the-art arts of the field. The objective is guiding the readers to a clear understanding of the past and current challenges and relevant issues in the area.
References