Genetically Engineered ART Architectures

Ahmad Al-Daraiseh¹, Assem Kaylani¹, Michael Georgiopoulos¹, Mansooreh Mollaghasemi¹, Annie S. Wu¹, and Georgios Anagnostopoulos²

¹ University of Central Florida, Orlando FL, 32816 michaelg@mail.ucf.edu
² Florida Institute of Technology, Melbourne, FL, 32796 georgio@fit.edu

Summary. This chapter focuses on the evolution of ARTMAP architectures, using genetic algorithms, with the objective of improving generalization performance and alleviating the ART category proliferation problem. We refer to the resulting architectures as GFAM, GEAM, and GGAM. We demonstrate through extensive experimentation that evolved ARTMAP architectures exhibit good generalization and are of small size, while consuming reasonable computational effort to produce an optimal or a sub-optimal network. Furthermore, we compare the performance of GFAM, GEAM and GGAM with other competitive ARTMAP structures that have appeared in the literature and addressed the category proliferation problem in ART.

12.1 Introduction

Adaptive resonance theory (ART) was developed by Grossberg (see [18]). Some of the ART architectures that have appeared in the literature include Fuzzy ARTMAP (FAM) (see [10]), Ellipsoidal ARTMAP (EAM) (see [1]), and Gaussian ARTMAP (GAM) (see [36]). All of these ART architectures possess a number of desirable properties, such as they can solve arbitrarily complex classification problems, they converge quickly to a solution (within a few presentations of the list of input/output patterns belonging to the training set), they have the ability to recognize novelty in the input patterns presented to them, they can operate in an on-line fashion (new input patterns can be learned by the ART system without retraining with the old input/output patterns), and they produce answers that can be explained with relative ease.

Since, Fuzzy ARTMAP’s inception in 1992, a number of ART related papers have appeared in the neural network literature, some of which (as the ones mentioned above) modified the Fuzzy ARTMAP neural network so as to improve its performance. A related, important contribution in the ART literature is the one contributed by Petridis and Kaburlasos in 1998 ([31]), where they introduced the Fuzzy Lattice Neural Network (FLNN), a cross fertilization of fuzzy set theory and lattice theory, which can handle general
types of data in addition to $N$-dimensional vectors. Most of the lattice work of Kaburlasos is included in a recently published book by Springer Verlag (see [21]) where a unified, cross-fertilizing approach for knowledge representation and modeling based on lattice theory is presented with emphasis on clustering, classification and regression applications. Some of Kaburlasos’ recent work related with fuzzy lattice reasoning (FLR), which is the algorithm/software applied on a FLNN, can be found in [22].

The above references paint only an incomplete picture of the work that researchers have contributed into the ART literature, since Fuzzy ARTMAP’s inception. However, since our goal in this chapter is to focus on the category proliferation problem in ART we are limiting, from this point on, our referrals to papers that have addressed this ART problem. Quite often the category proliferation problem in ART is connected with the issue of overtraining in ART. Over-training happens when ART is trying to learn the training data perfectly at the expense of degraded generalization performance (i.e., classification accuracy on unseen data) and also at the expense of creating many categories to represent the training data (leading to the category proliferation problem). Categories in ART are formed in order to compress the input data prior to mapping these compressed data to their respective outputs. The categories in Fuzzy ARTMAP are hyperboxes, in Ellipsoidal ARTMAP are ellipsoids, and in Gaussian ARTMAP they are Gaussian multi-dimensional probability distributions represented by their center points and widths (means and standard deviations) across every dimension. A number of authors have tried to address the category proliferation problem in ART. Amongst them we refer to the work by Marriott and Harrison, 1995, (see [28]), where the authors eliminate the match tracking mechanism of Fuzzy ARTMAP when dealing with noisy data; the work by Charalampidis et al., 2001 (see [13]), where the Fuzzy ARTMAP equations are appropriately modified to compensate for noisy data; the work by Verzi, et al., 2001 (see [35]), Anagnostopoulos, et al., 2002 and 2003 (see [2, 3]), and Gomez-Sanchez et al., (see [16, 17]), where different ways are introduced of allowing the ART categories to encode patterns that are not necessarily mapped to the same output (label); the work by Koufakou, et al., 2001, (see [25]), where cross-validation is employed to avoid the overtraining/category proliferation problem in Fuzzy ARTMAP; and the work by Carpenter, et al., 1998 (see [11]), Williamson, 1997 (see [37]), Parrado, et al., 2003 (see [30]), where the ART structure is changed from the winner-take-all to a distributed version and simultaneously slow learning is employed with the intent of creating fewer ART categories and reducing the effect of noisy patterns.

In this paper, we propose the use of genetic algorithms (see [15]) to solve the category proliferation problem in ART architectures, such as FAM, EAM and GAM.

Genetic algorithms (GAs) are a class of population-based stochastic search algorithms that are developed from ideas and principles of natural evolution. An important feature of these algorithms is their population based search