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Evolving intelligent algorithms for the modelling of brain and eye signals

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ABSTRACT

In this paper, the modelling problem of brain and eye signals is considered. To solve this problem, three important evolving and stable intelligent algorithms are applied: the sequential adaptive fuzzy inference system (SAFIS), uniform stable backpropagation algorithm (SBP), and online self-organizing fuzzy modified least-squares networks (SOFMLS). The effectiveness of the studied methods is verified by simulations.

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1. Introduction

In recent years, there are two important topics which are related with the modelling, they are the evolving intelligent systems and stable intelligent systems.

The evolving intelligent systems, are characterized by abilities to adjust their structure as well as parameters to the varying characteristics of the environment (with the term of environment embracing processes/phenomena with which the system has to interact and or deal with the users using the system) [6,46,20]. Some important results are given by [5,7–11,13,16,17,19,21–27,29,31,36–38]. In [5], two novel approaches for on-line evolving fuzzy classifiers are presented. In [7], an evolving system that considers the evolving clustering, online structure evolution and simplification is introduced. A hybrid evolving architecture for dealing with incremental learning is introduced by [8]. The suitability of various nature-inspired meta-heuristics to the problem of software testing is investigated by [9]. In [10], the authors follow an approach consisting of combining spectral clustering and ant colony optimization in a two-stage algorithm. In [11], the authors investigate self-adaptation of classification systems at three levels. The problem of the classification of streaming data from a dimensionality reduction perspective is addressed by [13]. A new approach for creating and recognizing automatically the behavior profile of a computer user is presented by [16]. The implementation of a zero-order Takagi–Sugeno–Kang (TSK)-type fuzzy neural network (FNN) is proposed by [17]. An evolving fuzzy granular framework to learn from and model time-varying fuzzy input-output data streams is introduced by [19]. A class of evolving fuzzy rule based system as an approach for multivariable Gaussian adaptive fuzzy modeling is considered by [21]. A new approach for evolving fuzzy modeling using tree structures is proposed by [22]. A new algorithm for incremental learning of a specific form of Takagi–Sugeno fuzzy systems is introduced by [23]. New approaches to handling drift and shift in on-line data streams with the help of evolving fuzzy systems (EFSs) are presented by [24]. In [25], the authors examine approaches for reducing the complexity of evolving fuzzy systems (EFSs) by eliminating local redundancies during training. A new methodology for conducting active learning in a single-pass on-line learning context is introduced by [26]. New dynamic split-and merge operations for evolving cluster models, which are learned incrementally and expanded on-the-fly from data streams are considered by [27]. In [29], the authors address option pricing using an evolving fuzzy system model and Brazilian interest rate options data. The use of evolving classifiers for activity recognition from sensor readings in ambient assisted living environments is described by [31]. In [36], a sequential adaptive fuzzy inference system called SAFIS is developed based on the functional equivalence between a radial basis function network and a fuzzy inference system (FIS). The performance evaluation of the recently developed sequential adaptive fuzzy inference system (SAFIS) algorithm for classification problems is presented by [37]. In [38], two adaptive

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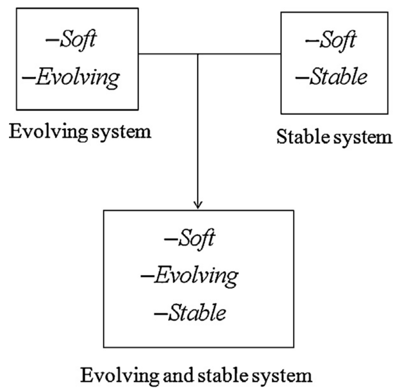

Fig. 1. Evolving and stable intelligent systems.

fuzzy control schemes including indirect and direct frameworks are developed for suppressing the wing-rock motion. The above systems are evolving and soft; however, they are not guaranteed to be stable.

The stable intelligent systems are characterized to be systems where some kind of stability is guaranteed, i.e., for bounded inputs in the algorithms, there are also bounded outputs and bounded parameters. Some important results are given by [1–4,32,33,35,40,41,47,50,51]. In [1], the authors proposes a new H∞ weight learning algorithm (HWLA) for nonlinear system identification via Takagi–Sugeno (T–S) fuzzy Hopfield neural networks with time-delay. New results on stability for Takagi–Sugeno fuzzy delayed neural networks with a stable learning method are introduced by [2]. In [3], an error passivation approach is used to derive a new passive and exponential filter for switched Hopfield neural networks with time-delay and noise disturbance. The model predictive stabilization problem for Takagi–Sugeno (T–S) fuzzy multilayer neural networks with general terminal weighting matrix are investigated by [4]. In [32,33], two stable intelligent controllers for nonlinear systems with dead-zone are addressed. Two stable neural networks are introduced by [35,40]. The aforementioned studies are stable and soft; nevertheless, they are not evolving.

There is research where evolving and stable characteristics are possible and also combined whenever assuring some sort of convergence to optimality given by [28,39,41]. That systems are novel because they merge the main characteristics of the above techniques into one algorithm which has the main characteristics to be evolving, soft, and stable. See Fig. 1.

This paper presents the comparison of three intelligent algorithms for the modelling of brain and eye signals. The signals could be applied for the patients who cannot move their bodies; therefore, they could use their brains or their eyes to say what they want or need. The algorithms are the SAFIS algorithm [36] which is an evolving intelligent system, SBP [40], which is a stable intelligent system, and SOFMLS [39], which is an evolving and stable intelligent system.

The paper is organized as follows. In Section 2, the SAFIS, SBP, and SOFMLS algorithms are detailed. In Section 3, the encephalography (EEG) and electro-oculogram (EOG) signals are described. In Section 4, the comparison of three algorithms for the modelling of brain and eye signals is presented. Section 5 presents conclusions and suggests future research directions.

2. Preliminaries

In this section the three algorithms of this paper are described.

2.1. SAFIS algorithm

A sequential adaptive fuzzy inference system (SAFIS) is developed based on the functional equivalence between a radial basis function network and a fuzzy inference system (FIS). In SAFIS, the concept of "Influence" of a fuzzy rule is introduced and using this the fuzzy rules are added or removed based on the input data received so far. If the input data do not warrant adding of fuzzy rules, then only the parameters of the "closest"(in a Euclidean sense) rule are updated using an extended Kalman filter (EKF) scheme.

The SAFIS algorithm is summarized as below [36]:

Given the growing and pruning thresholds e_g, e_p for each observation (x_k, y_k) where $x_k \in \Re^{N_x}$, $y_k \in \Re^{N_y}$ and $k = 1, 2, \ldots$, do

(1) Compute the overall system output:

$$\widehat{y}_k = \frac{\sum_{n=1}^{N_h} a_n R_n(x_k)}{\sum_{n=1}^{N_h} R_n(x_k)} \tag{1}$$

where

$$R_n(x_k) = \exp\left(-\frac{1}{\sigma_n^2}\left\|x_k - \mu_n\right\|^2\right)$$

where N_h is the number of fuzzy rules.

(2) Calculate the parameters required in the growth criterion:

$$\varepsilon_k = \max\left\{\varepsilon_{\max}\gamma^n, \varepsilon_{\min}\right\}, \quad 0 < \gamma < 1 \tag{2}$$

$$e_k = y_k - \widehat{y}_k \tag{3}$$

(3) Apply the criterion for adding rules:

If

$$\left\|x_k - \mu_{rn}\right\| > \varepsilon_k \tag{4}$$

and

$$E_{\inf}(N_h + 1) = \left|e_k\right| \frac{\left(1.8n\left\|x_k - \mu_{rn}\right\|\right)^{N_x}}{\sum_{n=1}^{N_h+1}(1.8\sigma_n)^{Nx}} > e_g \tag{5}$$

allocate a new rule with

$$\begin{aligned} a_{Nn+1} &= e_k \\ \mu_{Nh+1} &= x_k \\ \sigma_{Nh+1} &= n\left\|x_k - \mu_{rn}\right\| \end{aligned} \tag{6}$$

Else, adjust the system parameters a_{rn}, μ_{rn}, σ_{rn} for the nearest rule only by using the extended Kalman filter (EKF) method:

$$\begin{aligned} K_k &= P_{k-1}B_k\left[R_k + B_k^T P_{k-1} B_k\right]^{-1} \\ \theta_k &= \theta_{k-1} + K_k e_k \\ P_k &= \left[I - K_k B_k^T\right] P_{k-1} + qI \end{aligned} \tag{7}$$

where $\theta_k = \left[\theta_1 \cdots \theta_{rn} \cdots \theta_{Nh}\right]^T = [a_1, \mu_1, \sigma_1, \ldots, a_{rn}, \mu_{rn}, \sigma_{rn}, \ldots, a_{Nh}, \mu_{Nh}, \sigma_{Nh}]$.

Check the criterion for pruning the rule:

If

$$E_{\inf}(rn) = |a_{rn}| \frac{(1.8\sigma_{rn})^{N_x}}{\sum_{n=1}^{N_h+1}(1.8\sigma_n)^{Nx}} \tag{8}$$

remove the rnth rule, reduce the dimensionality of EKF.

end if

end if.

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