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Biological image classification using rough-fuzzy artificial neural network

Carlos Affonso [a,*], Renato Jose Sassi [b], Ricardo Marques Barreiros [a]

[a] Department of EIM, Universidade Julio de Mesquita Filho, UNESP, 18400-140 SP, Itapeva, Brazil
[b] Industrial Engineering Post Graduation, Universidade Nove de Julho, UNINOVE, 5001-100 SP, São Paulo, Brazil

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A B S T R A C T

This paper presents a methodology to biological image classification through a Rough-Fuzzy Artificial Neural Network (RFANN). This approach is used in order to improve the learning process by Rough Sets Theory (RS) focusing on the feature selection, considering that the RS feature selection allows the use of low dimension features from the image database. This result could be achieved, once the image features are characterized using membership functions and reduced it by Fuzzy Sets rules. The RS identifies the attributes relevance and the Fuzzy relations influence on the Artificial Neural Network (ANN) surface response. Thus, the features filtered by Rough Sets are used to train a Multilayer Perceptron Neuro Fuzzy Network. The reduction of feature sets reduces the complexity of the neural network structure therefore improves its runtime. To measure the performance of the proposed RFANN the runtime and training error were compared to the unreduced features.

1. Introduction

In complex problems as biological cells image classification, the capture of the essential features must be carried out without *a priori* knowledge of the image. The increased amount of attributes requires computational complexity and runtime even bigger. Moreover, due to noise in the database caused by excessive image features can cause a reduction in capacity of representation. According to Shang and Qiang (2008), the employment of Rough-Fuzzy features selection mechanism allows the reduction for a low dimensionality features sets from samples descriptions.

For these complex cases from the real life the use of Rough Sets (RS) in the pre-processing of the database has been efficient, since only the most relevant features are used as input parameters for the neural network. The RS has recently emerged as another major mathematical approach for managing uncertainty that arises from inexact, noisy, or incomplete information. It is found to be particularly effective in the area of knowledge reduction (Petrosino & Salvi, 2006).

In these cases, Fuzzy Set theory (FS) and RS represent two different approaches to vagueness. FS addresses gradualness of knowledge, expressed by the fuzzy membership, whereas rough set theory addresses granularity of knowledge, expressed by the indiscernibility relation (Affonso & Sassi, 2010).

An option to simplify the structure of the Artificial Neural Network (ANN) and reduce the noise caused by non-significant features is to use the Rough Set (RS) approach in order to select the most important features. The present paper proposes a new algorithm to realize the feature selection, with the intention to use RS as a tool for structuring the ANN. The methodology consisted of generating rules from training examples by rough-set learning, and mapping the dependency factors of the rules into the connection weights of a four-layered neural network.

The advantage of the Rough-Fuzzy Artificial Neural Network (RFANN) approach consists in the synergy achieved by combining two or more technical capabilities to achieve a more powerful system regarding to learning and generalization (Gomide, Figueiredo, & Pedrycz, 1998). A sequential architecture is used in this work, in which RS and the FS have distinct functions: RS identifies the most critical features, while the FS generates the surface response (input, output) since the Neuro Fuzzy Network (NFN) has Learnability and can adapt itself to the real world.

The paper is organized as follows: Section 2 presents the Literature review, Section 3 presents the Experimental Methodology and Section 4 presents the Conduct of Experiments. The Conclusion is presented in Section 5.

2. Literature review

Techniques can be combined to obtain a more powerful system in terms of interpretation, learning, parameter estimation, generalization, and less disability as well. Thus, various combinations have

* Corresponding author. Tel.: +551535249158.
E-mail address: affonso.unesp@gmail.com, affonso@itapeva.unesp.br (C. Affonso).

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been applied in different papers generating systems based on: Fuzzy Min–Max Neural Network, Regression Tree and the Random Forest model as a decision support tool for medical data classification (Seera & Lim, 2014), an hybrid evolutionary dynamic Neural Network for stock market trend analysis and prediction using unscented Kalman filter (Bisoi & Dash, 2014), credit risk evaluation using Multi-Criteria Optimization classifier with Kernel, Fuzzification and Penalty Factors (Zhang, Gao, & Shi, 2014), a novel Support Vector Machine model combining Kernel Principal Component Analysis with Genetic Algorithm is proposed for intrusion detection (Kuang, Xu, & Zhang, 2014), two independent hybrid mining algorithms to improve the classification accuracy rates of Decision Tree and Naïve Bayes classifiers for the classification of multi-class problems (Farid, Zhang, Rahman, Hossain, & Strachan, 2014), a novel Fuzzy Hybrid Quantum Artificial Immune Clustering algorithm based on cloud model (Zhang, Shan, Liu, & Zhang, 2014), an optimization approach based on the Ordinal Optimization Philosophy and Particle Swarm Optimization is used to search in the continuous space of the operational variables (Zhang, Chiang, & Wu, 2014) and a Local Least-Squares Support Vector Machines-Based Neuro-Fuzzy Model for Nonlinear and Chaotic Time Series Prediction (Miranian, & Abdollahzade, 2013).

Combined techniques can also be applied to the identification, treatment and processing of images, in generating systems based on: extreme Learning Machine and Sparse Representation based classification method, have attracted significant attention due to their respective performance characteristics in computer vision and pattern recognition (Luo & Zhang, 2014), a Neural-AdaBoost based facial expression recognition system (Owusu, Zhan, & Mao, 2014), Artificial Bee Colony approach to information granulation-based Fuzzy Radial Basis Function Neural Networks for image fusion (Yu & Duan, 2013), a novel Multi-Instance Learning algorithm based on Multiple-Kernels Framework has been proposed for image classification (Li, Wang, Zhao, Liu, & Wang, 2014), Fuzzy-Rough feature selection aided Support Vector Machines for Mars image classification (Shang & Barnes, 2013), Rough Sets and Near Sets in Medical Imaging (Hassanien, Abraham, Peters, Schaefer, & Henry, 2009), Implementation and comparative analysis of Rough Set, Artificial Neural Network and Fuzzy-Rough classifiers for Satellite image classification (Juneja, Walia, Sandhu, & Mohana, 2009) and an Analysis of Clustering Algorithms for MR Image Segmentation using IQI (Patel & Patnaik, 2012).

Hybrid techniques have been applied to biological images, generating systems based on: Expert System Approach to the Identification and Clustering of Features of Biological Images (Jordan & Perkins, 1988), Artificial Neural Networks for Classification and Identification of Data of Biological Tissue Obtained by Mass-Spectrometry Imaging (Xiong et al., 2012), Multi-objective Nature-Inspired Clustering and Classification Techniques for image segmentation (Bong & Rajeswari, 2011), Evolutionary Artificial Neural Network Design and Training for wood veneer classification (Castellani & Rowlands, 2009), Image Segmentation Algorithms applied to wood defect detection (Funck, Zhong, Butler, Brunner, & Forrer, 2003), a new Neuro-Fuzzy method to investigate the characteristics of the facial images (Diago, Kitaoka, Hagiwara, & Kambayashi, 2011), Rough Sets combined with various other methodologies such as Neural Networks, Wavelets, Mathematical Morphology, Fuzzy Sets, Genetic Algorithms, Bayesian Approaches, Swarm Optimization and Support Vector Machines in the image processing domain (Hassanien, Abraham, Peters, & Schaefer, 2008); Rough Set frameworks hybridized with other Computational Intelligence Technologies that include Neural Networks, Particle Swarm Optimization, Support Vector Machines and Fuzzy Sets (Hassanien et al., 2009).

2.1. Image identification

It takes a long time to train a person to be competent in wood identification. Furthermore, manual examination of the wood sample can be very subjective. In addition to the macroscopic features of wood, physical features such as weight (different moisture content), color (variation), odour, hardness, texture, and surface appearances are also considered. For unknown specimen, usually dichotomous keys are used on a systematic analytical procedure for the examination of the wood structure.

The identity of the tree in the forest can be easily known by examining their flowers, fruits and leaves. However, once the tree is felled, the identification of the tree becomes very difficult and has to rely on their physical, macroscopic and microscopic features for identification. In this research, an intelligent recognition system using low cost equipment for the identification of wood species based on the macroscopic features of wood has been designed (Pham, Soroka, Ghanbarzadeh, & Koc, 2006).

The image processing techniques are widely used for classification and clustering of plant cells. In most cases, the biological classification is performed by trained operators, but this solution suffers significant disadvantages, so the literature contains several papers in which neural networks are used in image processing plant cells (He, 1997; Khalid, Lee, Yusof, & Nadaraj, 2008; Marzuki, Eileen, Rubiyah, & Miniappan, 2008; Pham et al., 2006; Topalova & Tzokev, 2011), also for prediction of fracture toughness (Dassanayake, 2000; Samarasinghe, Kulasiri, & Jamieson, 2007).

2.2. Rough set theory (RS)

RS was proposed by Zdzislaw Pawlak in 1982 (Pawlak, 1982) as a mathematical model to represent knowledge and to treat uncertainty. An important concept in RS is the reduct.

A reduct is a minimal set of attributes that can represent an object with the same accuracy as the original set of attributes. Elimination of redundant attributes can help in the identification of strong, non-redundant classification rules.

A reduct of B – RED(B) – on information system (IS) is a set of attributes B'⊆ B such that all attributes a ∈ (B – B') are dispensable. Thus, U/INDs(B') =U/INDs(B), where INDs(B) is called the Indiscernibility Relation.

Computing the reduct is an n-p hard problem, and processing the reduct for large databases requires high computational processing. The reduct is generated by discernibility from the Discernibility Matrix.

The Discernibility Matrix of information systems S, denoted DM(B), is a symmetric n × n matrix with: $mD_{(i,j)} = \{a \in B \mid a(Ei) \neq a(Ej)\}$ for $i,j = 1,2,\ldots,n$. with $1 \le i, j \le n$ e $n = |U / INDs(B)|$.

Thus, the elements of the Discernibility Matrix mD(i,*j*) are a set of conditional attributes of B that differentiate the elements of classes in relation to their nominal values.

The reducts of S are generated through the simplification methods of Boolean functions for the Fs(B) function (1).

This simplification is an algebraic approximation of the logical functions, with the goal of reducing the number of attributes.

$$F_S(a_1^*, a_2^*, \ldots, a_m^*) = \wedge\left\{\vee m_D^*(i,j) \mid i,j = 1,2,\ldots,n, \qquad m_D(i,j) \neq 0 \right\} \tag{1}$$

With: $m_D^*(i,j) = \{a^* \mid a \in m_D(i,j)\}$

The discernibility function Fs(B) is obtained as follows: for all attributes represented by an element in the Discernibility Matrix MD(B), apply the sum operator ("or" or "∨") and, for each pair of cells in this matrix, apply the "product" element ("and" or "∧"), which results in a Boolean expression of "sum of products".

Fuzzy Sets concern membership among elements from the same class, while RS concerns the relationship between groups of elements in different classes.

However, the theory of RS does not compete with the Fuzzy Sets Theory but rather complements it. In fact, RS theory and Fuzzy