Engineering Applications of Artificial Intelligence 64 (2017) 172–186

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

Optimization of modular granular neural networks using a firefly algorithm for human recognition

Daniela Sánchez, Patricia Melin *, Oscar Castillo

Tijuana Institute of Technology, Tijuana, Mexico

ARTICLE INFO

Keywords:
Modular neural networks
Granular computing
Firefly algorithm
Human recognition
Ear recognition
Face recognition
Pattern recognition

ABSTRACT

In this paper a new optimization method for modular neural network (MNN) design using granular computing and a firefly algorithm is proposed. This method is tested with human recognition based on benchmark ear and face databases to verify the effectiveness and the advantages of the proposed method. Nowadays, there are a great number of optimization techniques, but it is very important to find an appropriate one that allows for better results depending on the area of application. For this reason, a comparison of techniques is presented in this paper, where the results achieved for ear recognition and face recognition by the proposed method are compared against a hierarchical genetic algorithm in order to know which of these techniques provides better results when a modular granular neural network is optimized and applied to pattern recognition mainly for human recognition. The parameters of modular neural networks that are being optimized are: the number of modules (or sub granules), percentage of data for the training phase, learning algorithm, goal error, number of hidden layers and their number of neurons. Simulation results show that the proposed approach combining the firefly algorithm with granular computing provides very good results in optimal design of MNNs.

1. Introduction

Human recognition based on biometric measures has allowed achieving better control or access to information or restricted areas, or simply to know the identity of a person (Kaur, 2016; Solanki and Pittalia, 2016). There is a plethora of works where different methods have been developed to find robust systems that provide security using biometric measures, such as face (Ch'ng et al., 2012), ear (Sánchez and Melin, 2014), fingerprint (Chandana et al., 2015; Sankhe et al., 2016), iris (Homayon, 2015), voice (Zhang et al., 2015), among others. Some of the main techniques used in the development of these works are neural networks (Haykin, 1994; Hassoun, 2003), fuzzy logic (Zadeh and Kacprzyk, 1992), data mining (Witten et al., 2011), evolutionary computation (Eiben and Smith, 2015), granular computing (Yao, 2005; Zhong et al., 2016), to mention only a few. Within of area of evolutionary computation, there is a wide variety of approaches as for instance; the already well-known genetic algorithm (GA) (Man et al., 1999; Holland, 1975), ant colony system (ACO) (Dorigo, 1992), particle swarm optimization (PSO) (Kennedy and Eberhart, 1995), or more recently, the cuckoo optimization algorithm (COA) (Rajabioun, 2011) or the firefly algorithm (FA) (Yang, 2009; Yang and He, 2013), among others. The combination of two or more of the above described techniques forms a hybrid intelligent system. These kinds of systems have been proposed in some works (Sánchez and Melin, 2014; Hidalgo et al., 2009; Martínez-Soto et al., 2015; Farooq, 2015), where better results have been achieved than when an individual technique is used. For this reason, in this paper a hybrid intelligent system is proposed, where techniques, such as modular neural network, granular computing and a firefly algorithm are combined.

A modular neural network is an improvement on the conventional artificial neural network (ANN), where if a task can be divided into sub-tasks each of these sub-tasks is learned by an expert sub-module. This technique has been successfully used in pattern recognition, particularly to human recognition using different biometric measures (Hidalgo et al., 2009; Pastur-Romay et al., 2016; Balarini et al., 2012; Basu et al., 2010). In this work, a modular neural network using a granular approach is used. Granular computing defines a granule as one of the numerous small particles forming a larger unit (Yao, 2005; Zadeh, 1998). This approach has been successfully combined with other areas (Bargiela and Pedrycz, 2006), and in the proposed method, granular computing is applied to granulate the information that the modular neural network is going to learn. This kind of neural networks was already proposed in Sánchez and Melin (2014), where a comparison among MGNN, MNN

* Corresponding author.
E-mail addresses: danielasanchez.itt@hotmail.com (D. Sánchez), pmelin@tectijuana.mx (P. Melin), ocastillo@tectijuana.mx (O. Castillo).

http://dx.doi.org/10.1016/j.engappai.2017.06.007
Received 21 October 2016; Received in revised form 7 April 2017; Accepted 5 June 2017
Available online 4 July 2017
0952-1976/

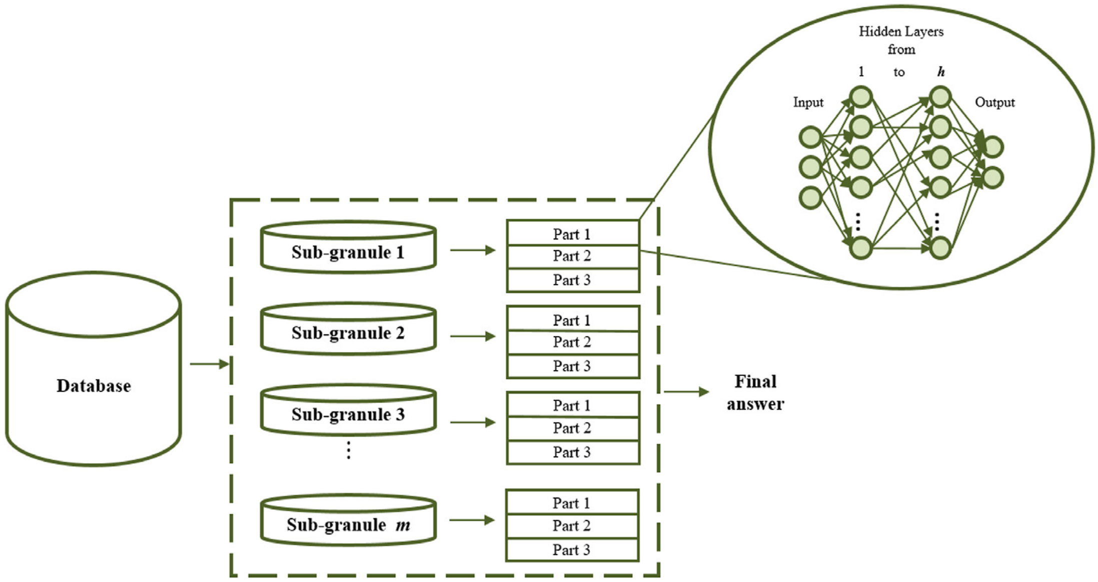

Fig. 1. The general architecture of the proposed method.

and ANN was performed and the advantages of MGNN were widely demonstrated. In that work the architecture of the MGNN was optimized by a hierarchical genetic algorithm (HGA). A HGA is an improvement to the conventional genetic algorithm, which has control genes to allow the activation and deactivation of genes and this allows solving complex problems (Raikova and Aladjov, 2002). In this paper, the contribution is the design of modular neural network architectures using a granular approach and these models are applied to human recognition based on the ear (Gutierrez et al., 2010) and face (Mendoza et al., 2010), but the proposed method can be applied to other biometric measures. The design of the MGNN is performed using a firefly algorithm, where the MGNN parameters must be found by the proposed algorithm, in this case the number of modules (sub granules), percentage of data for the training phase, learning algorithm, goal error, number of hidden layers and their number of neurons

This paper is organized as follows. The proposed method is described in detail in Section 2. The results obtained using the proposed method are presented and explained in Section 3. Statistical comparisons of results to measure the advantage of the proposed method are presented in Section 4. Finally, in Section 5, the conclusions and future work are offered.

2. Proposed method

The general architecture of the proposed method is described in this section; this method designs modular granular neural networks architectures using a firefly algorithm.

2.1. General architecture of the proposed method

The proposed method is based on modular neural networks with a granular approach. This kind of neural network was proposed in Sánchez and Melin (2014), where the advantages that these modular granular neural networks have over the conventional neural networks were presented, and basically this is because if a problem can be divided into smaller sub problems, each sub module (or sub granule) can be an expert on a part of the problem. In that work (Sánchez and Melin, 2014), the optimization of the MGNN was performed using a hierarchical genetic algorithm, and in this work a comparison between HGA and FA is performed to find out which of these techniques is better to perform the optimization. The main idea is to find the number of sub-modules (sub-granules) and each of these sub-modules is divided into 3 parts,

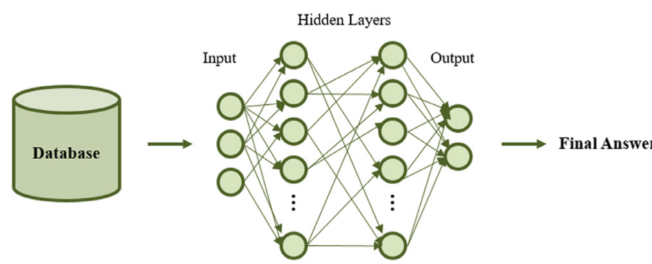

Fig. 2. An example of an artificial neural network.

because each image is also divided into 3 parts in a pre-processing process, and this part is going to be described later.

In Fig. 1, the granulation process also used in Sánchez and Melin (2014) is illustrated. A database represents a whole granule, and this granule is divided into sub granules, but each sub granule can have different size, and for these applications, it would be different number of persons learned by each sub module (sub granule).

2.1.1. Description of the modular granular neural network

The modular granular neural networks were proposed in Sánchez and Melin (2014), and the main difference between this kind of neural network and a conventional neural network is the division of a task into subtasks and then obtaining a final decision. In Fig. 2, an example of an artificial neural network is presented where a whole database is considered for its inputs and depending of the type of transfer functions outputs are obtained, so depending on the application a final output or result is achieved.

In Fig. 3, an example of a modular granular neural network can be found. As it was mentioned before this kind of neural network divides a task into subtasks. In this case, the whole database is a main granule, this granule can be divided into sub granules, and each sub granule represents the inputs of an independent neural network. The internal processes are the same as for a conventional neural network including the learning process, but for obtaining a final decision, the responses of modules (neural networks) must be combined or integrated. There are methods to perform this integration task, such as fuzzy integration, the winner takes all or a gating network.

In this work, each sub granule is divided into 3 sub modules as Fig. 1 shows, because the images are divided into 3 parts. To combine