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Interval type-2 fuzzy logic and modular neural networks for face recognition applications

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ABSTRACT

In this paper we present a method for response integration in multi-net neural systems using interval type-2 fuzzy logic and fuzzy integrals, with the purpose of improving the performance in the solution of problems with a great volume of information. The method can be generalized for pattern recognition and prediction problems, but in this work we show the implementation and tests of the method applied to the face recognition problem using modular neural networks. In the application we use two interval type-2 fuzzy inference systems (IT2-FIS); the first IT2-FIS was used for feature extraction in the training data, and the second one to estimate the relevance of the modules in the multi-net system. Fuzzy logic is shown to be a tool that can help improve the results of a neural system by facilitating the representation of human perceptions.

1. Introduction

In this paper we present the design and development of a new response integration method for multi-net systems applied to solve the face recognition problem. Because of the flexibility of neural networks, this method can be applied to a variety of applications of pattern recognition or temporal series prediction. Then we say that the method is general because it can be applied to the fusion of modular neural networks or neural networks ensemble combinations for different types of applications.

Many applications have high complexity because of the volume of the data; then some times a monolithic neural network is insufficient to process all the data or the performance achieved is poor. The design of multi-net systems can be a good solution for complex applications. Some problems can be solved with the modular approach inspired on the biological brain modularity, which focuses specific group of neurons for particular brain functions. In the ensemble approach neural networks can be combined in a redundant form, when each neural network can carry different performance, then a better result can be found if the results of several neural networks are combined [1,2].

At this moment, aggregation methods play a fundamental roll, because they can be capable of estimating the relevance of the multi-net components in order to obtain the best result for each particular application. The proposed method includes the fuzzy integral as aggregation operator and a fuzzy inference system for estimating the fuzzy densities. In fuzzy measures theory, fuzzy densities rate the relevance of information sources in multi-criteria decision making problems [3,4].

The main contribution of this paper is the proposed design of the generalized method for response integration in multi-net systems applied to a particular application for face recognition using modular neural networks. The Sugeno fuzzy integral is used for response integration in the integration unit of the modular network and an interval type-2 fuzzy system is used to rate the relevance of each module in the network. The use of fuzzy rules for estimating the relevance of information sources is another advantage of the proposed method because it allows the incorporation of expert knowledge into the process of rating the relevance of the modules.

The paper is organized in the following form. In Section 2 we explain the basics of multi-net systems, Sugeno measures, Sugeno integral and Sobel edge detection. In Section 3 we present an overview of the generalized method for response integration in multi-net systems. In Section 4 we describe the complete application of the method to solve the face recognition problem including a section for edge detection using Sobel operators and an interval type-2 fuzzy system. In Section 5 we show the obtained results and the comparison with other approaches for face

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recognition using the ORL (Olivetty Research Laboratory) face database.

2. Basic concepts

In this section the basic concepts of multi-nets systems, Sugeno measures, Sugeno integral and the Sobel operator are presented. These concepts are required to describe in a precise manner the proposed method for response integration in multi-net systems.

2.1. Multi-net systems

Multi-net systems can provide a solution to tasks, which either cannot be solved by a single net, or which can be more effectively solved by a system of modular net components. Similarly, better performance can be achieved when neural networks, as predictors, are redundantly combined [1].

It is important to make a distinction between ensemble and modular combinations. The term "ensemble" is the one commonly used for combining a set of redundant nets, although the term "committee" or "committee machine" has also been used for the same purpose.

By contrast, under a modular approach, the task or problem is decomposed into a number of subtasks, and the complete task solution requires the contribution of all the modules. Both the ensemble and modular combinations can exist at either a task or a sub-task level, as shown in Fig. 1 [1,2].

It is possible to identify four different modes of combining component nets. A distinction is made here between a cooperative and a competitive combination. The main difference is that in the cooperative combination it is assumed that all the elements to be combined will make some contribution to the decision, even if this contribution may be weighted in some way; whereas in a competitive combination, it is assumed that for each input the most appropriate element will be selected. In a sequential combination, the processing is successive; the computation of one module depending on the output of a preceding module. In a supervisory relationship, one module is used to supervise the performance of another module [5].

2.2. Sugeno measures

The Sugeno λ-measures are special monotonic measures defined as follows.

Definition 2. Let $X = \{x_1, \ldots, x_n\}$ be any finite set. A discrete fuzzy measure on X is a function μ: $2^x \to [0,1]$ with the following properties:

(1) $\mu(\phi) = 0$ and $\mu(X) = 1$;
(2) given $A,B \in 2^X$ if $A \subset B$ then $\mu(A) \le \mu(B)$ (monotonicity property).

The set X is considered to contain the names of sources of information (features, algorithms, agents, sensors, etc.) and for a subset $A \subseteq X$, $\mu(A)$ is considered to be the worthiness or relevance grade of this subset of information [3].

Definition 3. Let $X = \{x_1, \ldots, x_n\}$ be any finite set and let $\lambda \in (-1, +\infty)$. A Sugeno λ-measure is a function μ from 2^X to [0,1] with the following properties and Eq. (1):

(1) $\mu(X) = 1$;
(2) if $A,B \subseteq X$ with $A \cap B = \phi$, then

$$\mu(A \cup B) = \mu(A) + \mu(B) + \lambda\mu(A)\mu(B) \tag{1}$$

where $\lambda > -1$.

Eq. (1) is usually called the λ rule. When X is a finite set and the values $\mu(\{x\})$ called fuzzy densities, are given for each $x \in X$, these densities are interpreted as the importance of the individual information sources. The measure of a set A of information sources is interpreted as the importance of that subset of sources toward answering a particular question (such as class membership) [4].

The value of $\mu(A)$ for each $A \subset P(X)$, can be determined by the recurrent application of the λ rule. This value can be expressed with Eq. (2):

$$\mu(A) = \frac{[\prod_{x \in A}(1 + \lambda\mu(\{x\}))]}{\lambda} \tag{2}$$

We can observe that given the values of the fuzzy densities $\mu(\{x\})$ for each $x \in X$, the value of λ can be determined by the constraint $\mu(\{x\}) = 1$. Applying this constraint to Eq. (2) results now in Eq. (3):

$$\lambda + 1 = \prod_{i=1}^{n}(1 + \lambda\mu(\{x_i\})) \tag{3}$$

The parameter λ is specific to this class of measures and can be computed from Eq. (3) once the densities are known. Tahani and Keller showed that this polynomial has a real root greater than -1 and several researchers have observed that this polynomial equation is easily solved numerically. By property (1), specifying the n different densities, thereby reducing the number of free parameters from $2^n - 2$ to n.

The value of parameter λ is determined by the conditions of the following theorem [5]:

Theorem 1. *Let $\mu(\{x\}) < 1$ for each $x \in X$ and let $\mu(\{x\}) > 0$ for at least two elements of X. Then Eq. (3) determines a unique parameter λ in the following way:*

- If $\sum_{x \in X}\mu(\{x\}) < 1$, then λ is equal to a unique root of the equation in the interval $(0,\infty)$.
- If $\sum_{x \in X}\mu(\{x\}) = 1$, then $\lambda = 0$; that is the unique root of the equation.
- If $\sum_{x \in X}\mu(\{x\}) > 1$, then λ is equal to a unique root of the equation in the interval $(-1,0)$.

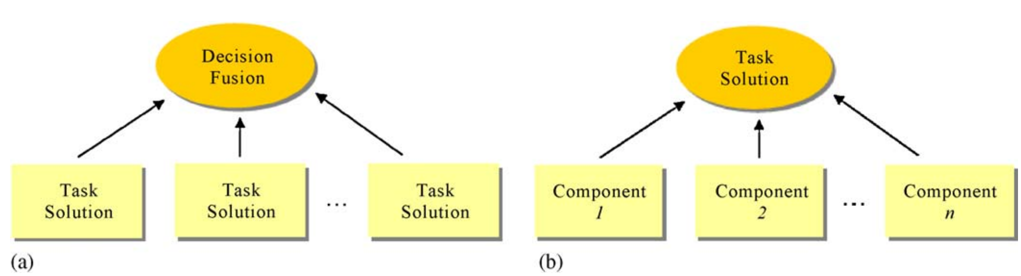

Fig. 1. Schemes of the two main multi-net system approaches: (a) Ensemble Multi-net System; (b) Modular Multi-net System.