A hybrid expert system for the diagnosis of epileptic crisis

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Abstract

This work presents a hybrid expert system (HES) intended to minimise some complex problems pervasive to knowledge engineering such as: the knowledge elicitation process, known as the bottleneck of expert systems; the choice of a model for knowledge representation to codify human reasoning; the number of neurons in the hidden layer and the topology used in the connectionist approach; the difficulty to extract an explanation from the network. Two algorithms applied to developing of HES are also suggested. One of them is used to train the fuzzy neural network and the other to obtain explanations on how the fuzzy neural network attained a conclusion. A case study is presented (e.g. epileptic crisis) with the inclusion of problem definition and simulations. The results are also discussed. © 2000 Elsevier Science B.V. All rights reserved.

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1. Introduction

In developed countries epilepsy affects 0.5–1% of the general population. This rate rises 1–3% in underdeveloped societies. In Brazil there are 1,400,000–4,200,000 epileptic patients. Fortunately, 60–80% of epileptics may have their seizures completely controlled after being correctly diagnosed and treated with rational use of modern anti-epileptic drugs [1].
Presently, the poor information which is presented to the physician may lead to misdiagnosis and to an unsatisfactory control of the crisis, and may result in unnecessary leaves or absence at work (due to the crisis), in segregation at school, at work and in the family, in unnecessary admissions in public hospitals and/or in psychiatric institutions, and in early retirement due to impairment. All these problems are caused by the lack of information, and are treated similarly — a great amount of public resources is spent. Consequently, the patients are subjected to great strain in their search for medical aid, and the state run offices which are supposed to provide support are negligent.

With the great evolution in computer science, mainly in artificial intelligence (AI), some of the problems encountered by the epileptic patient may be solved with the development and establishment of hybrid systems [2,3–7].

2. Methodology

The first stage in developing the proposed methodology, i.e. the basic rules and the set of examples, represents the knowledge acquisition (KA) task. The basic rules can be improved by capturing the uncertainties associated with the human cognitive process. The proposed model uses fuzzy logic [8]. The second stage corresponds to the neural network based expert system (NNES) implementation. The basic rules relate the concepts (neurons) that are used to establish the topology of the NNES and employ AND/OR graphs that help in developing the basic structure of this system. NNES structure that is able to receive several kinds of semantic variables, i.e. Boolean, linguistic, and quantitative inputs, may be seen in Fig. 1.

These inputs are converted by a fuzzification unit into a unique kind of fuzzy-type variable, which are the inputs of the NNES. Explicit defuzzification is not necessary because it is performed by the assigned semantics of the outputs of the NNES. It is believed that this sort of structure deals with modelling a structure through a simpler way and also by consuming less learning time than a traditional structure. Moreover, we have developed a learning algorithm (e.g. GENBACK algorithm), inspired by the classical back-propagation, that provides modifications in the connection weights as well as in the network structure by generating and/or eliminating connections. The third stage consists of the

![Diagram of NNES structure](uncorrected-proof.png)

**Fig. 1. Variable kinds of states.**
NNES refinement, which is accomplished through a learning algorithm using the examples of real cases as training set. This learning algorithm allows for structural changes of the network through inclusion and/or exclusion of connections and, eventually, of neurons belonging to the hidden layer. In this case, it is suggested that optimization in the hidden layer be accomplished using genetic algorithm (GA) [3,4,7,9].

After the NNES is refined, a reverse process is followed toward the inferring of the if–then rules together with their membership degrees. So that, based in [10], we have developed a new technique that can better accommodate if–then rules inferred with their membership degrees, i.e. a technique for extracting rules from a trained fuzzy NNES called fuzzy rule extraction (FUZZYRULEXT) which provides explanations of the results achieved by the NNES. Finally, Fig. 2 shows a general view of the HES proposed.

3. Algorithms for training and explaining the hybrid expert system (HES)

3.1. Steps of the GENBACK algorithm

1. Creation: individuals of a population. Gauss distribution was applied;
2. Codification: chain of chromosomes. Using a fixed chain of chromosomes with 8 bits;
3. Training: based on back-propagation algorithm;
4. Evaluation: using the fitness functions, e.g.
   \[ F_1 = \frac{N_{CH}}{\text{ERROR}} \]  
   \[ F_2 = \frac{1}{(N_{CH} + \text{ERROR})} \]

where \( F_1 \) and \( F_2 \) are the fitness function or objective function or cost function, \( N_{CH} \) is the neurons number in the hidden layer of the NNES, ERROR is the error in the NNES output;
5. Application of the roulette wheel process;
6. Ordering: each individual in a population;
7. Application: selection, crossover, mutation;
8. New generation;
9. Return to pass 3: winner NNES.

For the FUZZYRULEXT algorithm some steps are:
1. Choose an input–output pattern;
2. Select those neurons \( i \) in the preceding layer that have a positive impact on the conclusion at output neuron \( j \);
3. Let the selected set of \( m_i \) neurons of the hidden layer be denoted as \( \{a_1, a_2, \ldots, a_{m_i}\} \) and let their connection weights to neuron \( j \) in the output layer be given by the set
   \[ \text{wet}_{(n-1)i} = \{w_{(n-1)i}a_1, w_{(n-1)i}a_2, \ldots, w_{(n-1)i}a_{m_i}\} \]  
4. Determine the set of accumulative link weights \( \text{wet}_{(n-1)i} \) to neuron \( i \) in the hidden layer along the maximum weighted path be
   \[ O(i) > 0 \text{ and } w_{(n-1)i}a_k > 0 \]
   \[ \text{wet}_{(n-1)i} = \max|\text{wet}_{(n)i}a_k + w_{(n-1)i}a_k| \]
5. Select the set of input neurons as \( m_l = \{a_1, a_2, \ldots, a_{m_l}\} \);
6. Arrange net impact (NI) of the elements of the set of weights obtained in the last pass in decreasing order, e.g. \( \text{NI}_{(n-1)i} = O(i) \times \text{wet}_{(n-1)i} \);
7. Select \( l_s \) input neurons for the clauses with \( w_{(n-2)i}a_k > 0 \) and \( l_p \) input neurons remaining with \( w_{(n-2)i}a_k < 0 \), such that \( m_l = |l_s| + |l_p| \);
8. Determine clause generation: for a neuron \( l_{sl} \) in the input layer, selected for clause generation, the corresponding input feature \( u_{sl} \) for Boolean or numeric inputs is obtained as \( u_{sl} = (l_{sl} - 1) + 1 \);

The antecedent of the rule is given with the numeric or Boolean property being determined

\[
\text{prop} = \begin{cases} 
-0.8, & \text{if } u_{sl} \leq -0.8 \\
1, & \text{if } u_{sl} = 1 \\
-0.8 < x < 1, & \text{otherwise}
\end{cases}
\]
The corresponding input feature $u_{sl}$ for linguistic inputs is obtained as $u_{sl} = (I_{sl} - 1) \mod 3 + 1$.

The antecedent of the rule is given with the linguistic property being determined as

$$\text{prop} = \begin{cases} 
\text{strong}, & \text{if } u_{sl} \geq 0.8 \\
\text{moderate}, & \text{if } -0.4 < u_{sl} < 0.7 \\
\text{weak}, & \text{if } u_{sl} \leq -0.4 
\end{cases}$$

The certainty measure for each output neuron is defined as

$$\text{bel}_j = O_{(n+1)j} - \sum_{i \neq j} O_{(n-1)i}$$

The consequent of the rule is given with the property being determined as

$$\text{prop} = \begin{cases} 
-0.8, & \text{for } -5 \leq \text{bel}_j \leq -0.2 \\
1, & \text{for } \text{bel}_j > -0.2 \\
\text{not recognize}, & \text{for } \text{bel}_j < -5 
\end{cases}$$

The process is repeated until the if–then rules are determined to justify all outputs presented by the input–output patterns of the trained NNES.

9. Determine elimination process of redundant rules: to determine the total number of rules generated in the last stage; to create one vector for the input–output data; to compare antecedent–consequent of each rule for determining how many rules are alike; to keep those rules that are distinct; to eliminate those redundant rules; to determine the total number of rules generated without redundancies.

4. Simulations

The case study illustrates the HES application to the problem of epilepsy diagnosis. The epilepsy data bank was supplied by physicians working, mainly, at the University Hospital of Federal University of Santa Catarina, Brazil. The data bank contained 36 symptoms and four diagnostic classes.

Given a min–max NNES with three layers, i.e. an input layer (e.g. symptoms), an output layer (e.g. diagnosis), and a hidden layer, the activation function for each neuron is chosen as the hyperbolic tangent since the range of values of the min–max ANN is often constrained on $[1, -1]$. Sometimes the values for generation number, initial population, Gauss distribution, crossover rate, mutation rate, learning rate, momentum, tolerance, maximum epochs, and total epochs were also altered. In most cases, with this training data, satisfactory results were obtained. It was also observed that the quality of the NNES was improved. In this case, the value of relative variance coefficient (RVC), e.g. $\text{RVC} = \text{standard deviation/average value}$, decreased, while the fitness increased. We also observed that the standard deviation curve reached higher values than in previous simulations. So variable (fitness) dispersion in relation to average of this variable (fitness average) increased. There was a great occurrence of crossover and mutation in some generations occurred.
In Fig. 3 we show the generation of a simple rule looking at inputs (symptoms) $S_1, S_2, \ldots, S_6$ and outputs (diagnosis) $D_1, D_2,$ and $D_3$.

One sample set of weights $w_{ji}$ and $w_{il}$, the activation of inputs $S_i$, and the values of membership degrees are demonstrated. Applying the FUZZYRULEX algorithm to this case the following rule was extracted: if $S_2$ and $S_3$ and $S_6$ then $D_2$.

Finally, we validated the HES by applying the sensibility (SENS) and specificity (SPEC) concepts, which are defined in [11]. The results obtained for clinical cases of epileptic crises classification varied from 67 to 83% (see Table 1). Other cases may be found in [5,7]. The results were similar.

Table 1
“Real problem” — classification of epileptic crisis

<table>
<thead>
<tr>
<th>S</th>
<th>NIL</th>
<th>NHL</th>
<th>NOL</th>
<th>DST</th>
<th>NGRWR</th>
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<th>NR</th>
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</tr>
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</table>

*S — simulations; NIL — number of neurons in the input layer; NHL — number of neurons in the hidden layer; NOL — number of neurons in the output layer; DST — data set of test; NGRWR — number of generate rules with redundancies; NGRWOR — number of generate rules without redundancies; NR — number of hits; PR — percentage of hits.*
5. Conclusions

As characteristics of the HES we can mention:
1. A KA Stage which is more promising than those applied to a traditional ES;
2. A training algorithm inspired in the classical back-propagation one, i.e. GENBACK, which uses concepts of GA for, eventually, optimising the hidden layer of the NNES;
3. An extraction algorithm of fuzzy rules, i.e. FUZZYRULEXT, which is used to obtain the explanation on how the network arrived to a conclusion. In this case, it is possible to build an explanatory system of the NNES.

It was also observed that the HES, applied to a real problem, demonstrated that in the test sets of patterns presented to NNES the majority was recognised; the extraction technique of fuzzy rules achieved also satisfactory values; the system was capable of translating the encoded knowledge among the various connection weights of the NNES in rules. Besides, all examples applied to test the FUZZYRULEX algorithm demonstrated that the procedure for reduction of the number of redundant rules developed in this work, after the learning and refinement stages of the NNES, were suitable.

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References