A Hybrid Fuzzy-Neural Expert System for Diagnosis

Christoph S. Herrmann *
Intellektik, Informatik, TH Darmstadt
Alexanderstrafie 10, D-64283 Darmstadt, Germany
herrmann@intellektik.informatik.th-darmstadt.de

Abstract

Fuzzy Logic, a neural network and an expert system are combined to build a hybrid diagnosis system. With this system we introduce a new approach to the acquisition of knowledge bases. Our system consists of a fuzzy expert system with a dual source knowledge base. Two sets of rules are acquired, inductively from given examples and deductively formulated by a physician. A fuzzy neural network serves to learn from sample data and allows to extract fuzzy rules for the knowledge base. The diagnosis of electroencephalograms by interpretation of graphoelements serves as visualization for our approach. Preliminary results demonstrate the promising possibilities offered by our method.

1 Introduction

Repetitively applied cognitive tasks of recognizing and evaluating certain phenomena, called diagnostic tasks, are among the main applications for Artificial Intelligence (AI). As there exists a vast variety of such diagnostic tasks in medicine, it has always belonged to the spectrum of potential users of Artificial Intelligence.

Most popular among AI methods in medicine are knowledge based systems [Buchanan and Shortliffe, 1985], modeling the diagnostic behaviour of experts. A variety of such expert systems is being used in everyday practice of physicians since Shortliffe introduced MYCIN [Shortliffe, 1976], an expert system designed to diagnose infections of the human blood. One of the greatest difficulties in designing a convenient expert system is acquiring the knowledge base. We introduce a new approach where a dual source knowledge base is generated by deductive and inductive learning.

Neural networks have also made their way into diagnosis. They are able to learn relationships between data sets by simply having sample data represented to their input and output layers. In the field of pattern recognition in medical data, neural network based approaches have led to quite remarkable results, for example in processing MRI pictures [Hall *et* a/., 1992] or EEG traces [Mamelak *et* a/., 1991; Jando *et* a/., 1993]. For the task of acquiring knowledge bases, which is a part of our hybrid approach, neural networks have been proposed recently [Thrun and Mitchell, 1993].

Fuzzy logic [Zadeh, 1965] also makes its appearance in medicine, dealing with the uncertainty of verbal expressions [Kuncheva, 1991; Nishimura *et* a/., 199l]. Terms like *many, few* or *probably* are hard to model with conventional logic. The linguistic variables offered by fuzzy representations allow pseudo-verbal descriptions close to natural human expressions.

All of the above methods bear advantages as well as disadvantages as will be seen in Section 2. Combining these methods not only sums up the advantages but also avoids some of the disadvantages. Up to now, only few approaches in medical diagnosis combine multiple methods of Artificial Intelligence, although good results have been made by these means, modeling a physician's decision process [Kuncheva *et* a/., 1993; Orsier *et* a/., 1994].

Here, we will describe a hybrid system consisting of a fuzzy expert system for rule-based reasoning with a fuzzy neural network for acquiring case-based knowledge in addition to the explanation-based knowledge from an expert (Section 3). The automatic acquisition of rules by the network is implemented in parallel to the classical formulation of expert rules. Two modes of processing result for the hybrid system: A learning mode to feed the knowledge base and an execution mode diagnosing patient data. All components of the system are based on a fuzzy representation, serving as an interface notation between the components and making a fuzzification of input data necessary.

In Subsection 3.2, a very effective mapping technique will be introduced, transforming fuzzy variables into a neural representation.

To visualize the processing of real medical data in such a system, we chose the diagnosis of electroencephalograms (EEGs) for demonstration. This type of medical data, measured and stored electronically, is very well suited for automatic processing since it need not be converted to an electronic representation any more. Other types of data will also be appropriate for diagnosis in our system. We will describe our sytem apart from the application as far as possible and propose related topics

*also affiliated with Mainz University Clinic, Department of Neurology, Reisingerweg, D-55101 Mainz, Germany

and Mc Clelland, 1986]). Therefore, to represent multiple phenomena eight neurons would be required for each phenomenon. Since the number of features contained in every time-slice varies through the EEG (not every sample is deranged by an artifact) a representation is needed which is capable of coding multiple phenomena in a constant number of neurons.

We have developed a mapping scheme that brings two fuzzy variables into a network suited representation by calculating the cross product, which is described in detail in [Herrmann, 1995a]. The two four-term fuzzy variables result in 16 neurons $Nf_{requencyXamplitude}$ (see figure 2). Each neuron represents the conjunction of two fuzzy terms of each variable, thus overcoming the binding problem. The activation value of a neuron is calculated via the algebraic product of the two represented membership functions:

$$N_{delta \times zero} = \mu_{delta} * \mu_{zero} = 0.6 * 0.6 = 0.36$$

The sum of activation, resulting from one spectral phenomenon always sums up to 1 for sake of reinterpretability of the rules learned by the network.

3.3 Fuzzy Neural Network

The fuzzy features, presented to the neural network by the two-dimensional mapping method, are then trained to be detected by the net. In order to extract the acquired knowledge, a fuzzy-neural network, called FuNe [Halgamuge and Glesner, 1993; Halgamuge *et al.*, 1993], is used in our three layer network. The special multilayer perceptron architecture is trained with a gradient descent algorithm. There exist three types of neurons in the middle layer grouped together topographically. One group of neurons can perform only the *or* function of multiple inputs while another group only performs the *and* function. As there may as well be unary rules, composed of simple one-term-premises, there is a third group of neurons having single inputs and single outputs. The output neuron simply acts as an *or* function of all middle neurons. In the initial state the fully interconnected network represents all possible logical functions of *or* premises, *and* premises, and the 16 *unary* premises. During the learning process all connections below a certain threshold are eliminated. This pruning method has been proposed by Le Cun in 1990 [LeCun *et al.*, 1990] in order to increase learning speed—but, it is also useful for limiting the number of resulting rules. This is of special interest to us, because we will extract exactly these rules after the training and want to avoid rules with negligible rule strength.

A net trained to detect bulbus artifacts is shown in its final state in Figure 2. As an example, the pattern at the input neurons represents a bulbus artifact (ba) in a simplified manner [2]. The delta frequency component is high while all other frequency components are low. The artifact is detected in the output neuron, shown by its activation of 1. Some of the inputs no longer contribute to the detection task at all, since their low-weight connections have been pruned.

[2] For the sake of simplicity we used only values 0 and 1, although they will not occur in reality.

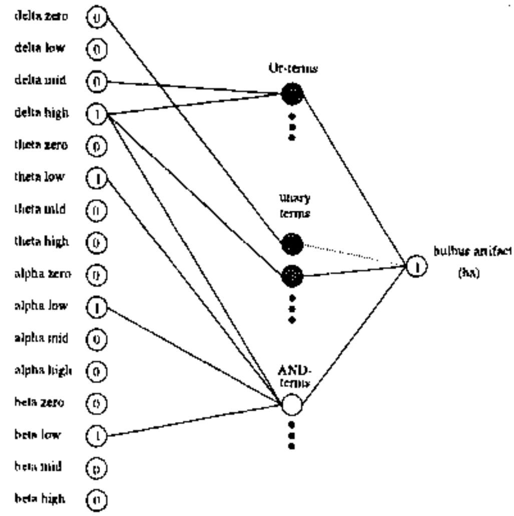

Figure 2: Neural network after completed training

Rules (1) to (3) are extracted from the three shaded neurons of the network and build up part of the knowledge base for the fuzzy expert system.

(1)	IF	delta mid OR delta high	THEN	ba
(2)	IF	delta zero	THEN	NOT ba
(3)	IF	delta high	THEN	ba

These rules do not all contribute to the result in the same way, which is expressed by different rule strengths. The strength of a rule is computed from the weight of the connection between the neuron representing the rule and the output neuron. Rule (2) has a negative strength indicating a negation of the conclusion (dashed line in Figure 2).

3.4 Fuzzy Expert System

The heart of our hybrid system is a fuzzy expert system, called FuzzyCLIPS [Knowledge Systems Laboratory, 1994], derived from CLIPS [Artificial Intelligence Section, 1993]. This expert system consists mainly of three components (see Figure 1, 'Fuzzy expert system'), the *dual source knowledge base* containing the combined rule sets from inductive and deductive learning, the *user knowledge base* where the actual phenomena of a patient are entered, and the *inference mechanism* concluding a diagnosis from the comparison of the knowledge base.

When acquiring rules for the knowledge base of an expert system two major learning paradigms apply: deductive learning and inductive learning. Deductive learning mostly is carried out by explanation-based learning [Minton *et al.*, 1990], meaning that the system is tought which rules lead to the desired decision capability. Inductive learning is applied when this knowledge is incomplete but examples may serve as a teacher for machine learning techniques [Michalski, 1983]. Our knowledge base consists of two seperately acquired sets of rules. The first one is acquired deductively from an expert by explanation-based learning. The second one is acquired inductively by machine learning in a neural network. The resulting dual source knowledge base integrates two autonomous rule sets. They might contain rules that are equal in premises and conclusion but different in the degree of certainty, which results in contradiction in the worst case. Like Holland proposed in 1986 [Holland, 1986], we do allow these contradictory rules, postulating it as a natural feature of decision processes and thus being well suited to model those. The following example might shed some light upon this matter:

Wife rule: IF evening THEN go home
Boss rule: IF evening THEN stay in office

If one equally obeys to wife and boss (equal rule strengths) one certainly needs a third rule to make a decision, like

IJCAI rule: IF deadline close THEN stay in office

which contributes to one of the former conclusions. The same is supposed for our dual source knowledge base. There may very well be phenomena that exist in sample data but are described differently in the expert rules. In this case the resulting uncertainty has to be solved by different rule strengths or a further rule, manifesting one of the possible conclusions.

Besides an explanation component it is also important for this medical application that a *don't know* conclusion exists, telling the user if abnormal phenomena were detected but could not be interpreted.

4 Preliminary Results

When talking about results in medical diagnosis, we would first like to mention one major point in where to put the main focus. Other than in common detection tasks it is not sufficient to simply watch the overall performance of the system in means of average error, like it would be appropriate for character recognition, for instance. The diagnosis performance must be split into the missing of phenomena, called false negatives, and the accidental finding of phenomena which are not actually present, called false positives. With these two measures it is possible to decide whether the two can be kept apart or will be overlapping. For certain diagnosis types, it is very important to have absolutely no false positives whereas a few false negatives were still acceptable, like in diagnosing cerebral death. Vice versa, in other cases it is important to have no false negatives, like in diagnosing epileptic seizures for emergency purposes. (Both examples were chosen from the class of EEG diagnosis tasks.)

Figure 3 shows a typical diagram illustrating false positives (dashed line) versus false negatives (solid line) as a function of the threshold *e* (FP/FN-diagram) for the detection of bulbus artifacts (BAs). Since we apply fuzzy logic, we get fuzzy results rather than discrete ones. (We do not use standard defuzzification.) The example shows the diagnosis of bulbus artifacts in EEGs. The decision of the system, whether it is a bulbus artifact or not, is represented by an analog value in the range from 0 to 1. For a binary decision a threshold is needed, above which a BA is assumed. In Figure 3 there is a wide gap between

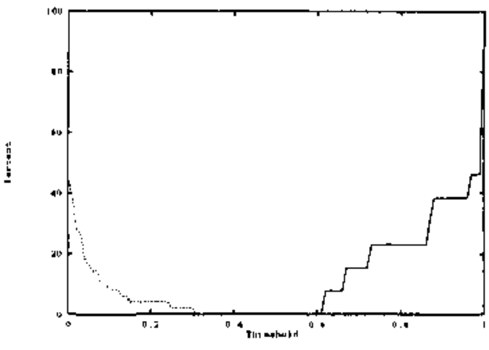

Figure 3: False positive BAs (dashed) and false negative BAs (solid) of a patient record containing no other artifacts than bulbus artifacts

false positives and false negatives (0.3 - 0.6). A threshold centered in this gap will assure a high probability for neither diagnosing false positives nor false negatives.

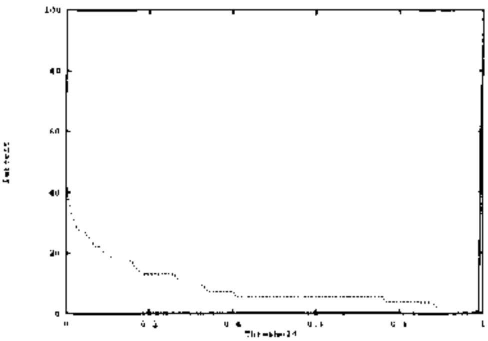

Figure 4: False positive BAs (dashed) and false negative BAs (solid) in a patient record with additional electrode artifacts

The example of Figure 4 nicely demonstrates the degree of accuracy of the system. The diagram shows only a narrow gap for the threshold, proposing possible misses in future data. The system can correctly diagnose all existing bulbus artifacts in the patient record with ease, shown in the narrow band of false negatives (rightmost peak in Figure 4). Nevertheless, the wide scope of false positives gives rise to the assumption that the diagnosis performance is of minor quality, since with a threshold of *e* — 0.5 , 10% diagnosed BAs would not actually be such. Retrospectively examined, it showed that those false positives were indeed BAs, but of minimal amplitude and thus overlooked in the visual diagnosis. Only the 1.8% false positives that remained up to a threshold of e = 0.94 were not BAs but electrode artifacts, being graphoelements that are somewhat related to BAs in terms of frequency and amplitude and can only be kept apart due to their shape. Thus, without explicitely comparing the system and a human expert yet, we showed with these preliminary results that the system's precision is of competing accuracy.

The comparison of the two rule sets, serving as basis for the dual source knowledge base, brought up two interesting results.

- The inductively generated rule set, extracted from the network, contained more rules than the one deductively acquired from the expert. These extra rules seem redundant at first glance, because the expert can easily distinguish between different phenomena on the basis of more obvious criteria. But for the electronic system, designed to diagnose a vast variety of phenomena, it may very well be of great importance to 'know' every extra description neglected by the expert.
- The extracted rules were more precise in their degree of fuzzy membership, since they were actually calculated from examples.

For our example of the bulbus artifact, the physician formulated the rule:

(4) IF frequency=delta and amplitude=high THEN ba

The automatically generated rule base contained a whole group of rules with different rule strengths. The premises, conclusions and rule strengths are shown in the following table (compare to the network connections in figure 2). Only the rules with rule strenghts (RS) above 1.0 are listed, while rules with lower rule strengths were pruned.

PREMISE	CONCLUSION	RS
delta mid OR delta high	ba	1.75
delta zero	NOT ba	1.51
delta high	ba	2.73

This detailed rule base is the reason, why the system was able to detect 10% low-amplitude artifacts (see figure 4). This would not have been possible with the mere expert rule (4).

5 Discussion

By combining three major methods of Artificial Intelligence into a single hybrid system we managed to combine most of their advantages, avoiding some of their disadvantages at the same time.

The hybrid system, described in this article, introduces the following new paradigms of modeling the cognitive task of diagnosis:

- Instead of either acquiring the whole knowledge base automatically from examples, being an inductive learning method [Michalski, 1983], or refining a rough knowledge base [Ourston and Mooney, 1994], being an enhanced explanation-based learning method [Minton *et al.*, 1990], we are using a dual source knowledge base. This knowledge base consists of two sets of rules, coexisting with equal importance, one generated deductively from rules formulated by an expert and another one generated inductively by machine learning in a neural network. This offers the full range of benefits from neural network learning. Additionally, the automatically acquired rules can be supervised and adapted in the expert system, eliminating the black box problem (see Subsection 2.2).
- The coexistence of the two resulting rule bases, with the possibility of competing knowledge, is not only permitted but desired. The competition of rules and the mechanism of taking further rules into account is part of the cognitive decision task.

Besides the integration of the existing fuzzy neural network and fuzzy expert system, some intelligent interfacing techniques are introduced, that might as well be used for different applications:

- A two-dimensional mapping technique, used to assign the membership values of linguistic variable terms to input layer neurons of a network. By this means, it is possible to input existing fuzzy representations into neural networks in order to autonomously acquire case-based knowledge from sample data (see Subsection 3.2).
- An application-specific fuzzification of spectral EEG data that will work for most other multidimensional data, especially other frequency domain data, like voice spectra in speech recognition, as well as all kinds of medical images (see Subsection 3.1).

Our preliminary results (see Section 4) point out some promising features:

- We proved the possible precision of our system, being more accurate than the human expert, when applied to the task of diagnosing bulbus artifacts in EEGs.
- Comparing the two rule sets of our dual source knowledge base it showed that the inductively acquired set was more extensive and of higher precision than the one deductively acquired.

In future we plan to investigate the interference effects of a dual source knowledge base. They occur when the two bases contain contradictory or similar rules with different rule strengths. For the case of perfect contradiction of two rules, possibly resulting in no conclusion, a third rule could be generated by a supervising mechanism to indicate to the user that such a contradiction occurred.

6 Acknowledgements

The author wishes to thank Andre de Waal for his last polish of the English, as well as Frank Reine and Michael Thielscher for their valuable comments on an earlier version of the paper.

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