A NEURAL NETWORK EXPERT SYSTEM TO SUPPORT DECISIONS IN DIAGNOSTIC IMAGING

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Abstract

An expert system module has been integrated into clinical workstations used for report generation and the storage and retrieval of diagnostic images. The expert system works in the background and supports the physician's decisions. The system has been created for ultrasound examinations of the abdomen, it will be transferred to other domains. The knowledge-based system has been implemented for the same knowledge segment using two different methods: a rule-based approach with the AI-tool Joshua on a Symbolics machine for prototyping and knowledge debugging, and a neural network approach based on backpropagation. Our results showed that the neural network was robust and flexible for the mainly associative knowledge found in our application; it performed well in general and, specifically, on subsets of findings entered during the course of an examination. We therefore decided to combine both components.

1. Objectives

"Intelligent" frontend workstations have been integrated with promising results into a system designed for documentation and information purposes in a clinical department of internal medicine. The clinical database system has been used since 1985 to store and retrieve results of endoscopy, ultrasonography, and other laboratory examinations. Among the features of the frontend workstations are automatic report generation, speech recognition, and storage and retrieval of digitized diagnostic
To support and guide the physician during the description of images and the generation of a report, a knowledge-based system has been integrated. Like Swett et al. [5], we considered it extremely important to integrate this module completely into the routine environment: the expert system works in the background, physicians use the same logic of input screens as before its introduction. The expert system will mainly be helpful to facilitate the step from description to interpretation. To support the cognitive process of describing findings, typical images may be displayed for comparison. In addition, images collected during the routine use of the system and stored together with their structured description, are used as input for a separate teaching system that has been implemented on a Macintosh. These components have been created for ultrasound examinations of the abdomen. Transferability to other domains (such as endoscopy) was one of the design principles of the system, so it may be seen as a prototype for the support of the description and interpretation of diagnostic (and therapeutic) procedures involving imaging in general.

2. Methods and Technical Approach

2.1. System architecture

We use a frontend-backend concept with networked workstations under UNIX, X11, OSF/Motif and the C language. Images are stored on an "optical" server via NFS. The distributed relational database management system INGRES runs on the database backend and on the frontends. The UNIX tools 'lex' and 'yacc' are used to build generators for structured input forms, reports, and rules. The neural network module is completely implemented in C [4]. A rule-based system has been built in parallel and independently on a Symbolics machine under the artificial intelligence tool Joshua [6]. The intention was to port its functionality to the frontend workstations. The attached teaching module has been implemented on an Apple Macintosh using a hypertext tool.

2.2. Description of the system's functionality

The user interface is based on menus offering descriptions of findings. Items are selected via mouse, keyboard, or speech recognizer. The system performs the following main actions:
- Ranking of differential diagnoses for the given findings
- Display of additional input-triggered questions
- Display of suggestions of further diagnostic procedures
- Explanations of derived results
- Display of typical images

After all findings have been entered, a report is generated and printed. Images that have been selected are stored together with the description of the findings and the diagnoses.

2.3. Development of the knowledge-based system

The knowledge-based system has been implemented for the same knowledge segment (liver diseases) using two different methods: a rule-based approach with the AI-tool Joshua on a Symbolics machine for prototyping and knowledge debugging, and a neural network based on backpropagation. First results showed that the neural network was robust and flexible for the mainly associative knowledge found in our application. We therefore decided to combine both components by using a neural network design with additional explicitly stated rules.

2.4. Neural network architecture

The neural network for the symptoms and diseases of the liver consists of a 3-layer feed-forward network with backpropagation of error signals [4]. All units of one layer are fully connected to all units of the next layer. Input neurons correspond to symptoms (i.e. attribute-value pairs from the input menus like "echo texture homogenous", "attenuation positive"), while output neurons correspond to diagnoses. There are about 100 diagnoses in the complete system. For the implemented diagnosis of liver diseases we use 80 input neurons and 30 output neurons, with 60 neurons in the hidden layer. After each new item entered, a new ranking of diagnoses is calculated and, based on this ranking, rules triggering additional questions may be fired. After the completion of the input, a final ranking of differential diagnoses is displayed. As in the case of additional questions, rules are again used to suggest the next procedures appropriate for diagnosing the most likely disease(s). Since images are stored together with their structured description, it is possible to show typical images for each disease. Entered findings are checked for inconsistencies before they are propagated through the neural network. Only 0 and 1 have been used as input
values for case descriptions. This approach excludes the possibility of uncertainty or grading in the description of symptoms, although it could be used easily with the neural network design. The output values of the neural network range from 0 to 1 and are divided into 4 categories. The final weights of diagnoses are:
- probable diagnosis
- suspected diagnosis
- differential diagnosis only
- unlikely diagnosis.

2.5. Knowledge acquisition and maintenance

As a first step, rules for the description of liver diseases were agreed upon by senior physicians. These rules lead to diagnoses or suspicions from combined observations, present necessary conditions for diagnoses, and suggest additional diagnostic procedures. The tool Joshua was used for knowledge debugging. It offers both forward- and backward-chaining rules and several models of truth maintenance systems (TMS). A variety of options based on Joshua's LTMS [2] have been employed: checking why a conclusion was derived, asking "what-if" questions, checking why a specific diagnosis could not (yet) be derived. Our prototype uses 180 rules.

For the neural network, two types of training sets have been used: "prototypical profiles" are based on input values in the [0,1] interval, that express typical regularities seen in a large number of cases for a disease. "Case profiles" using only 0's and 1's as input values report the presence or absence of a given symptom in an actual case. For both types of profiles, output activations for all considered diseases are given: even for concrete cases it is possible that more than one final diagnosis results from the examination and that several differential diagnoses must be considered. All values have been based on experts' judgements. In this stage of our development we decided to control the knowledge base explicitly (e.g. by checking if the rules hold in the neural network training data) and did not try to automatically generate a knowledge base from patient cases.

The fact database has been implemented, maintained, and updated using the relational database management system INGRES. INGRES tools are used to check if the previously acquired rules are fulfilled in the input files for the neural net. Additional consistency checks are carried out to detect facts with similar symptom activations but differing diagnosis activations.

The training algorithm is based on the generalized delta rule minimizing a root mean
squared error function. We use a constant learning rate and momentum term to adjust the weights after each presentation of a pattern. For our current number of 350 training profiles, the training procedure requires about 10 hours at an HP 80486 computer under SCO Unix, with the convergence criterion that the deviation between expected and actual output values is less than 10% for all output nodes.

At the moment, explanation components are better understood in rule-based systems than in neural network systems. Our actual explanation component uses the initially acquired sets of sufficient and necessary conditions for the derivation of diagnoses or the display of changing activation levels during the input of findings.

3. Results

Knowledge acquisition and debugging have been carried out for the same knowledge segment using a rule-based approach and a neural network approach.

During this acquisition phase, it became clear that the domain knowledge is mainly associative. As a consequence, the construction of a neural network with input nodes corresponding to findings and output nodes corresponding to diagnoses became feasible. The input nodes have been mapped to items of the structured input forms. Items not clearly distinguishable under objective criteria (especially gradings like "ascites present" or "ascites massive") have been mapped to the same input neuron. It had to be considered that physicians might describe the same disease in different ways, as for example with inhomogeneous steatosis of the liver or liver metastases which might be described as diffuse or circumscript. An evaluation showed that the description of images by structured forms is feasible in our domain. Variation between 5 physicians describing the same cases (10 cases from videotape) was minimal. As a result, knowledge acquisition based on structured input forms is possible and we could have proceeded to an automatic generation of knowledge directly from cases.

The formalization of knowledge based on rules is an approach that matches the way physicians tend to express their knowledge. A disadvantage lay in the possible lack of completeness, especially regarding facts physicians internalize and do not consider worth mentioning. Its advantages were a clear formulation of the main relationships and an explicit handling of the system's knowledge and actions, which was even improved by the tool Joshua. The graphical display of the knowledge base was not too helpful in a domain with a comparatively shallow level of knowledge.
Known advantages of a neural network approach [3] have proven important for our application: its flexibility and generalization features performed well for variations in disease presentation that had not yet been expressed in the knowledge base. In addition, the system performed well on subsets of findings entered during the course of an examination. A rule, in contrast, is fired only when all elements in the conjunction of a premise are fulfilled.

An evaluation on a non-formal basis of the network using about 350 fact profiles has been carried out. Data of 20 real cases have been entered into the system and the system's final ranking has been compared with the actual diagnoses in these cases (confirmed by physicians not involved in the development of the system). Identical results for the main diagnosis were found in 17 cases, while in the remaining 3 cases, the correct main diagnosis ranked second or third.

4. Discussion

A neural network expert system has been implemented to guide and support the physician during the evaluation of sonographic images. Although to date no final evaluations have been made, initial results can be presented.

We found that the description of images by structured forms is feasible in our domain and that a neural network is capable of deriving diagnoses from this input. For the mainly associative knowledge found in our domain, the neural net approach displays some advantages over a rule-based system. The flexibility and generalization features of the neural network approach resulted in a system that performed well for variations in disease presentation as well as on subsets of findings.

We have been able to build a hybrid system using rules and a neural network component, but some questions are still open. The explanation component is still simple and has not yet been tested formally. Because of the parallel construction of a rule-based system and a neural network for testing purposes, we were able to use rules for consistency checks among the elements of the training sets for the neural network. We have not yet used an automatic generation of a knowledge base. Experiments to build or improve a knowledge base by direct input of case knowledge from our routine database will follow.

Formal evaluations of the system's performance are required. Our work on the
problem of multiple diseases found during one examination has been successful but not yet finalized. We are planning to connect several networks for the description of other organs (kidneys, spleen etc.).

Acceptance by physicians is high, especially when the system is combined with a teaching component. We are working on the transfer of the system to other domains involving diagnostic imaging.

References