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An Intelligent Medical System for Diagnosis of Bone Diseases

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Abstract

In this paper, aspects of the design of an intelligent medical system for diagnosis of bone diseases that can be detected by scintigraphic images are presented. The system comprises three major parts: a user interface (UI), a database management system (DBMS), and an expert system (ES). The DBMS is used for manipulation of various patient data. A number of patient cases are selected as prototype and stored in a separate database. Diagnosis is performed via the ES, called XBONE, based on patient data. Knowledge is represented via an integrated formalism that combines production rules and a neural network. This results in better representation, and facilitates knowledge acquisition and maintenance.

1. Introduction

Computer-based methods are increasingly used to improve the quality of medical services. Those methods include both conventional techniques, such as database management systems (DBMSs), and artificial intelligence (AI) techniques, such as knowledge-based systems (KBSs) or expert systems (ESs) [1, 6].

Medical diagnosis is a very active field as far as introduction of the above techniques is concerned. In medical diagnosis, DBMSs are used for storing, retrieving and generally manipulating patient data, whereas ESs are mainly used for performing diagnoses based on patient data, since they can naturally represent the way experts reason. Diagnosis of bone diseases is greatly facilitated by the use of nuclear medicine methods, more specifically by the use of scintigraphic images (or scintigrams or scans)[1], and a number of relevant expert systems have been developed [2, 7].

In this paper, an intelligent medical system for diagnosis of bone diseases that uses the above methods is presented. The structure of the paper is as follows. In section 2 the medical knowledge involved is outlined. In section 3 the architecture of the system is discussed. Section 4 deals with the knowledge representation formalism used by the ES. Finally, section 5 concludes.

2. Medical Knowledge

2.1 Patient Data

Patient data concerns information related to the patient and can be distinguished in three types: demograhic, clinical and nuclear medicine (NMI) data. *Demographic data* concerns

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[1]Terms interchangeably used.

information such as patient's age, sex etc. *Clinical data* is further distinguished in physical findings and laboratory results. *Physical findings* are those detected by a physical examination of the patient, like e.g. the existence and the kind of a pain etc. L*aboratory results* are those detected via laboratory tests, like e.g. blood tests etc.

Finally, *NMI data* is that extracted from scintigraphic images. The images are acquired by a γ-camera and depict the concentration of an administered radio-pharmaceutical (99m Tc-MDP) on patient's osseous tissue. NMI data concerns description of the concentration patterns depicted in the scintigrams. Description consists in an account of two types of observed features, qualitative and quantitative.

2.2 Heuristic knowledge

Heuristic knowledge represents experience accumulated through years and concerns the way an expert uses the above knowledge to make diagnoses. A diagnosis basically consists in relating patient data with corresponding diseases. Especially in the case of the NMI data, a physician should recognise the *characteristic patterns* of the radio-pharmaceutical concentration in the scintigrams. Each pattern gives an indication of the category of the suspected bone disease. Diagnosis of bone diseases is two-fold. An initial diagnosis is made based on the demographic and clinical data of the patient. This is then used either to specify the kind of the scan needed (simple or 3-phase) or to be compared with a later diagnosis based on the NMI data. This later diagnosis may or may not coincide with the initial. It is then up to the doctor to decide which is the right one.

3. System Description

The architecture of the system is illustrated in fig.1. It consists of three major parts: a User Interface (UI), a Data Base Management System (DBMS) and an Expert System (ES), called XBONE.

The DBMS is used to manipulate patient data. Scintigrams acquired by a γ-camera are transferred to the system. Although a γ-camera is typically accompanied by a dedicated computer, we developed an interface with a PC [5] so that acquired images can be directly introduced into the system and stored into the Patients Database (PDB) via the Data & Image Manager (DIM). The rest of the patient data is also introduced in the PDB by the user-physician.

A number of patient cases are selected from the PDB as *prototype cases* by the user-physician, after final diagnoses have been made, and stored in the Prototype Cases Database (PCDB). The selection is based on a standard protocol [10]. Prototype cases are also classified according to the disease category they concern. They are then used to identify characteristic scintigraphic patterns for each category and subcategory of the diseases.

The ES is used to perform diagnosis. The Knowledge Base (KB) contains the heuristic knowledge for diagnosing bone diseases. An integrated knowledge representation (KR) formalism based on production rules, the most widely employed KR formalism by ESs [3], is used (see next section). There are two rule sets in the KB, one dealing with the initial diagnosis and the other with the later one. The Working Database (WDB) contains the case-specific data, that is the (initial) patient data, partial conclusions, data given by the user, and any other information relevant to the case under consideration. Patient data are transferred from the PDB. The Inference Engine (IE) uses the available knowledge to draw conclusions and make diagnoses. The Explanation Mechanism (EM) creates explanations when asked by the user to do so. The Training Mechanism (TM) is used for rule training (see next section).

Finally, the UI performs a number of functions. It allows interaction with the PDB and the PCDB through the DIM, so that the user can manipulate patient data and the prototype cases. Also, the user can interact with the IE to start a diagnosis process as well as with the EM to ask "why" and "how" questions during the process. Finally, the user can use the TM to perform rule training.

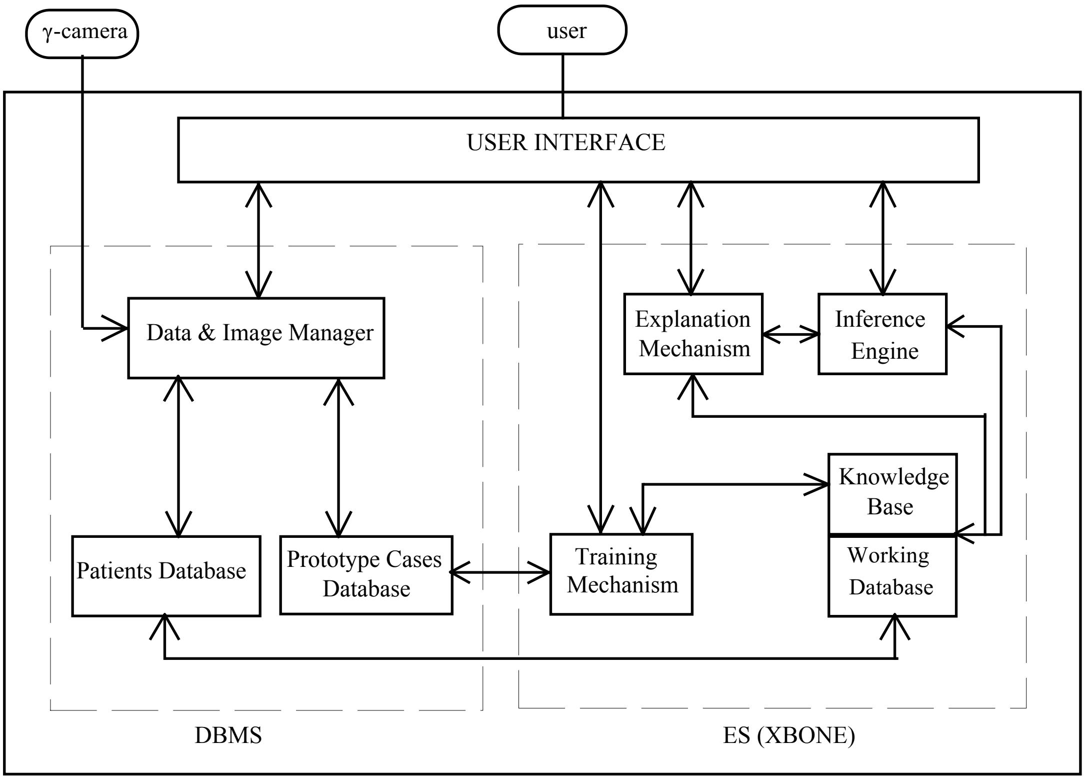

Fig.1 The Architecture of the System

4. Knowledge Representation in XBONE

4.1 Motivation

A situation met in medical diagnosis is the following. There are a number of symptoms (i.e. patient data) that all contribute in diagnosing a disease. However, not all of the symptoms have the same significance. For example, a symptom S1 may give much stronger evidence for diagnosing a disease D than a symptom S2. Also, some combinations of symptoms may give stronger evidence than others in diagnosing the disease. To be able to represent this situation in a production rules formalism, we introduce a factor assigned to each condition of a rule, representing its significance in drawing the conclusion. To determine the values of and manipulate those factors, the adaline unit (see e.g. [4, 8]) is employed.

4.2 The Integrated Formalism

Each rule is considered as an adaline unit (fig.2). The inputs c_i, i=1,...,n of the unit are the conditions of the rule. Each condition c_i is assigned a number sf_i, called a *significance factor*, corresponding to the weight of the input of the adaline unit. Moreover, each rule itself is assigned a number sf_0, called the *bias factor*, corresponding to the weight of the bias input (c_0 = 1) of the unit. Each input takes a value from the following set of discrete values:

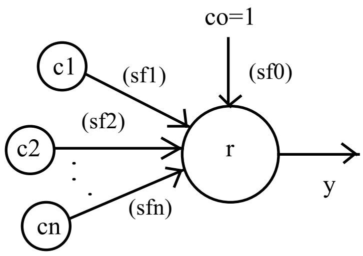

Fig.2. A Rule as an Adaline Unit

$$c_i = \begin{cases} 1 & \text{if condition is true} \\ -1 & \text{if condition is false} \\ 0 & \text{if value is unknown} \end{cases}$$

This gives the opportunity to distinguish between the falsity and the absence of a condition, in contrast to conventional rule-based systems. The output y is calculated as the weighted sum of the inputs filtered by a threshold function [4, 8]. Thus, the output can take one of two values, '0' and '1', representing failure and success of the rule respectively.

The general syntax of a rule is the following[2]:

<rule> ::= [(<bias-factor>)] **if** <conditions> **then** <conclusions>

<conditions> ::= <condition> {**and** <condition>}

<conclusions> ::= <conclusion> {**and** <conclusion>}

<condition> ::= <object> <l-operator> <value> [(<significance-factor>)]

<conclusion> ::= <object> <r-operator> <value>.

<object> acts as a variable and represents a concept in the domain. <l-operator> and <r-operator> denote a symbolic (e.g. is, isnot) or a numeric operator (e.g. <, >=). <value> denotes a value of the <object>, numeric or symbolic. Finally, <bias-factor> and <significance-factor> are real numbers. Since significance factors are optional, conventional production rules can be used.

The factors assigned to the rules are determined by the TM. Each rule is individually trained. To this end, a number of prototype training patterns, called the *training set*, are supplied for each rule. For example, [0 1 1] could be a training pattern for the rule **if** S1 **and** S2 **then** D. The standard LMS learning algorithm [4, 8] is used.

5. Conclusions

In this paper, an intelligent medical system for diagnosis of bone diseases that can be detected by scintigraphic images is presented. The system is still under development by the collaboration of the Depts of Computer Engineering & Informatics and Nuclear Medicine of

[2] A BNF notation is used here, where '[]' denotes optional occurrence and '{}' zero, one or more occurrences of the enclosed expression. Also, '<>' denotes a nonterminal symbol. All other symbols are terminal.

the University of Patras (e.g. [9]), and it is intended for use by nuclear medicine physicians. It is currently implemented in the C language on a PC.

A DBMS is used for patient data manipulation. Scintigrams are directly acquired by the system. However, NMI data are extracted by the user-physician. Although there are systems using computer-based methods for NMI data extraction [7], image processing techniques are not very reliable, due to the inherent noise and the very large number of possible normal and abnormal situations, so that extraction of the NMI data by the physicians is preferred [2]. The prototype cases can be used for characteristic patterns standardisation for each category of diseases.

An expert system is used for performing diagnosis. Knowledge is represented via a formalism integrating production rules and the adaline neural network. This results in better representation, since one can represent more complex relations between conditions (symptoms). Because determination of the significance factors is automated, knowledge acquisition is also partially automated, thus helping the experts to express their knowledge. All that an expert has to do is to determine the symptoms involved in diagnosing a disease and the training set. Also, KB maintenance is easier, since rules can be periodically trained using the updated PCDB.

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