A SERIAL MODEL FOR COMPUTER ASSISTED MEDICAL DIAGNOSIS

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SUMMARY

In this paper we discuss a simple model for an interactive consultation system for medical applications. That system was developed to provide consultative advice on diagnosis of arthritis, but it could be easily applied to a different class of diseases. We examine in particular how the determination of the appropriate sequence of diagnostic tests that have to be performed on the patient can be optimised by the use of a decision table, in which the medical knowledge is shown. We begin with a review of features which were seen to be essential to a consultation system for medical applications and we suggest how these requirements imply program design criteria. This is followed by a formal explanation of the proposed model and its fundamental assumptions. The last part of the paper is then devoted to a report of our experience with the experimental computer system.

RÉSUMÉ

On étudie dans cet article un modèle simple de système de consultation médicale interactive. Ce système a été mis au point pour donner des avis concernant le diagnostic des arthrites mais on pourrait l'adapter facilement à une autre famille de maladies. On examine en particulier comment la détermination de la suite appropriée de tests, à faire subir au patient, peut être optimisée en utilisant une table de décision où les connaissances médicales sont incorporées. On commence par passer en revue les traits qui ont été considérés comme essentiels pour un système de consultation médicale et on apporte des suggestions sur la manière dont ces exigences impliquent des critères concernant l'élaboration des programmes. Suit alors une explication formelle du modèle proposé ainsi que de ses hypothèses fondamentales. La dernière partie de l'article est enfin consacrée à la présentation de l'experience faite avec le système de calcul expérimental.

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I. INTRODUCTION

In recent years an increasing amount of research in automatic medical diagnosis has been done. Several methods have been developed to assist the physician during the diagnostic process.

The diagnostic problem for the physician can be considered as constituted globally by two phases:

(1) the determination of the appropriate sequence of diagnostic tests to perform on the patient in order to collect information;

(2) the development of a diagnosis from a given set of clinical signs.

The two phases are strictly interconnected and a diagnostic decision cannot be taken without a complex process of combination of them. Usually the determination of the tests and the development of a clinical decision from their results are repeated until a reliable decision can be taken.

This paper aims at proposing a model to assist the physician during the determination of the appropriate sequence of tests. The model presented here is based on a serial acquisition of facts about the patient. The initial observation of some attributes on the patient allows the separation of a particular class of diseases among which to constrain the medical decision. Starting from this point the proposed model operates on the description of the diseases of the selected class to determine the best sequence of diagnostic tests necessary for the clinical decision. The serial process of test outcomes acquisition updates, after each observation, the knowledge of the patient situation. The domain of the diseases is so reduced, excluding those not consistent with the obtained results.

The procedure continues until a diagnostic decision can be safely taken. In this way the attention is mainly focused on the problem of selecting the most suitable test to apply. Note that the selection is based on the medical knowledge about the diseases, as well as on the already ascertained knowledge about the patient. The formal representation of the presented model is then given, using the state-space approach of problem solving, and the algorithm for the solution, based on the stepwise refinement idea, is illustrated.

An experimental computer system implementing the model has been written and tested on different cases. An example is presented in which this program is used for arthritic diseases.

II. ANALYSING THE MEDICAL DIAGNOSTIC PROBLEM

The practical importance of studying and developing computer aids for medical diagnosis is obvious. An increasing amount of research has been done in this

area and several methods have been developed to assist the physician during the diagnostic process (Lusted, 1968; Schwartz *et al.*, 1973).

Recently, cognitive psychology and artificial intelligence researchers have also become interested in the structure of medical knowledge and the processes by which it is manipulated as examples of general knowledge structures and problem-solving processes (Gini and Gini, 1973; Shortliffe, 1976).

This paper attempts to fit the problem of medical diagnosis into the framework of problem-solving theory of artificial intelligence (Nilsson, 1971) and in particular explores special algorithms to reduce the number of diagnostic tests needed to develop reliable medical decision. We can conceptualise the diagnosis problem as a recognition problem (Fahlman, 1973). In particular a medical diagnosis system is presented with a group of signs, symptoms, test results, facts, and its job is to come up with a diagnosis, an identification of a disease or several diseases whose manifestations most closely match the condition of the patient (Lusted, 1968; McNeil *et al.*, 1975). Because of the interest in the process, the model of diagnosis which will be used here is based on a serial acquisition of facts about the patient (Fries, 1970; Gorry, 1967; Gorry and Barnett, 1968). Thus we require the diagnosis system to have some preliminary hypotheses about the patient's disease, to constrain the recognition problem within a specified class, and we expect that these hypotheses will become more and more precise after the addition of each new piece of information.

We will point out that the knowledge in the diagnostic system is dynamic and during the course of the session is continuously updated by the addition of new information. When the session starts, all the elementary hypotheses have the same possibility, because no particular disease has been suggested by the patient symptoms. As more detail is presented, certain hypotheses become stronger by virtue of their correlation and ability to account for present findings (Pople, 1971; Rubin, 1975).

The first problem that arose in developing a representation for diseases was how to account for the great variability in individual cases while extracting a general description of the mechanisms of dysfunction. Our initial work was deliberately restricted to a well-defined, circumscribed medical problem, that was important enough to attract interest from researchers and would serve as a demonstration prototype. The second problem we faced was how to obtain the knowledge acquisition, which tests to perform, when, in which order and so on, to collect information about the patient.

The discrimination power of a test, its ability to rule out and to support the presence of a number of diseases, generally differs from moment to moment, as each moment corresponds to a different accumulated information. Some tests may be quite well suited for separating the members of some specific subset of diseases, and therefore performing such a test makes sense at the stage of the

decision making process where the probability of the presence of that subset is sufficiently high. Other tests may be much more suitable to distinguish between different groups of diseases but have no specific discrimination power to individuate some particular disease.

In considering an ordered test sequence the physician should weigh the expected value of the tests against the cost of them. On the one hand he attempts to minimise the consequences of possible misdiagnosis, while on the other hand he aims at keeping the number of costly and dangerous tests as low as possible. In searching for the optimal solution to this problem, different starting points are possible, generally leading to different solutions (Barnoon and Wolve, 1972; Schwartz *et al.*, 1973).

A way of minimising the number of tests to perform on the patient is to minimise hypotheses about the patient disease by rejecting unlikely ones. One method of rejection is to include in disease descriptions some rejecting symptoms, whose presence precludes that disease's existence. A scoring algorithm may be used to evaluate the tests according to their significance in the recognition process. The algorithm we developed takes into account both positive and negative evidence for a hypothesis and scores are normalised by being divided by their highest possible total score. Another important point is that some tests are significant only for some diseases, not for others. These tests will give a positive or negative contribution only to the hypotheses for which they are significant, while no contribution will be given to the other hypotheses. In addition, we could assign a priori probabilities to diseases. The age and sex of a patient affect this probability profoundly. Combining age, sex and disease leads to a useful number representing the probability of the disease occurring in a patient of particular age and sex. This number will be considered as a weight associated to the disease and will influence the evaluation of the scores. It is important to notice that the proposed algorithm is based on a scoring mechanism, and it works independently by the way in which the score has been computed.

The last problem we had to face was how to consider the outcomes of the test. In our system all observations are quantised and binarised so that tests may be only true, false or undetermined. When the result of a test is obtained, the test becomes true of false, before it is undetermined. This assumption is sometimes too strong and different values of tests, for instance ranging from 0 to 1, could most closely match the physician reasoning process.

Clinically it is sufficient to use but a few quantification levels, corresponding to the interpretation of never, sometimes, often, usually, almost always, always. To deal with those levels minor changes would be required in our system; the basis of the scoring algorithm would anyway be the same. In this direction we may envisage a possible future improvement to the system, but that's not the main point of this presentation. We would like to underline again how the

algorithm we developed can fastly be modified to take into account new considerations, and so, the software system implementing it.

Let us now start explaining in greater detail the formal representation of the model and the description of the scoring algorithm.

III.   SEQUENTIAL COMPUTER DIAGNOSIS

We will present in this section the model used for the medical diagnosis in our system. As indicated above, the model is based on a sequential acquisition of facts about the patient.

Strategies for minimising diagnostic errors vary greatly depending upon the type of error to be attacked. According to Fries (Fries, 1970), the selection of the most helpful diagnostic signals from a large quantity of noisy data is more crucial than the exact method chosen to analyse the signals. It may be important to reduce the number of diagnostic tests employed to the minimum number required to establish a diagnosis at a given level of certainty in the particular patient. The following model suggests a method for selecting a minimal yet sufficient number of relevant symptoms for any individual patient. Before entering in this description we will define the notation used throughout the paper. This notation is presented in Table 1.

We consider particularly important to list explicitly all the underlying assumptions supposed to be valid in our model. In that way we hope a deeper understanding and analysis of our proposal will be achievable. These assumptions are listed above in Table 2.

The description of the set D of possible diseases with respect to the set S of symptoms characterising the diseases of the set D is represented by means of *disease-symptoms relations* in the *medical knowledge base* (MKB).

TABLE 1
DEFINITION OF THE NOTATION

Notation	Meaning
D	Set of possible diseases
d_i	ith disease of the set D
N	Number of different diseases of the set D
S	Set of symptoms characterising the diseases of the set D
s_j	jth symptom of the set S
M	Number of different symptoms of the set S
T	Set of available tests
t_r	rth test of the set T
Q	Number of different tests of the set T
P_i	Set of different disease-symptoms relations corresponding to the disease d_i
p_{ki}	kth relation in the set P_i of relations corresponding to the disease d_i
v_r	Observed outcome of the rth test performed on the patient
c_t	Cost of performing the test t_r
MKB	Set of disease-symptoms relations for all the diseases of D

TABLE 2

Assumptions

1. The set D of possible diseases is known and fixed and all diseases are different
2. Each element d_i of D is a set of disease-symptoms relations, corresponding to the different observable patterns of the disease d_i
3. The patient has one and only one of the diseases of D, possibly none
4. Each pair of diseases differs in at least one symptom, the presence or absence of which can be revealed by one of the available tests
5. The set T of the available tests is known and fixed and all tests are different
6. Each test t_r of T is characterised by two possible outcomes (yes/no) meaning the presence or absence of it
7. All tests remain available for execution during an unlimited time period
8. The outcome of any test can be determined with certainty
9. There is one test for each symptom, so that the set of tests T and the set of symptoms S have the same cardinality and are in biunivocal correspondence

Each relation describes a chunk of knowledge expressed in a highly stylised form as a logical combination of facts, the presence or absence of symptoms for a specified disease. In that way the diseases are simply expressed as a logical combination of different symptoms.

Assumptions: A disease d_i can be expressed as a logical combination of symptoms, as for instance

out = arthritis AND attacks AND (tophi OR (NOT tophi AND uricemia))

where AND, OR and NOT have the usual logical meaning.

We may express the same combination as a logical disjunction of relations:

gout = arthritis AND attacks AND tophi OR
        arthritis AND attacks AND uricemia AND NOT tophi

each relation being the kth relation in the set P_i of the relations corresponding to the d_i disease.

In the shown example the set P_i has only two elements, namely

p_{1i} = arthritis AND attacks AND tophi
p_{2i} = arthritis AND attacks AND uricemia AND NOT tophi

Note that each disease-symptoms relation contains only the logical connective AND and NOT, corresponding to the fact that it expresses the situation of presence or absence of symptoms for a particular disease.

The MKB is constituted by all the disease-symptoms relations corresponding to all the diseases of the set D. This structured form makes it easy the examination of the knowledge by other parts of the system (Gini and Gini, 1975).

However, since we want to deal with a simple and efficient implementation of the model in a computer system, we avoid the explicit use of logic expressions and we represent the knowledge in a slightly different form, very easily understandable.

We will use a three dimensional array as a suitable data structure for the medical knowledge. The entries in the array are:

(a) the M elements of the set S, the symptoms;

(b) the N elements of the set D, the diseases;

(c) for each element d_i of D, the set P_i of the disease-symptoms relations. Since the cardinality of those sets P_i is not the same some elements of the array are meaningless and are not used.

The array expressing the MKB, which we will shortly call MKB, is illustrated in Fig. 1. In each element of it, MKB (i, j, k) a symbol is stored:

(a) Y(es), if the symptom s_j has to be present for the disease d_i in its p_{ki} description;

(b) N(o), if the symptom s_j has not to be present for the disease d_i in its p_{ki} description;

(c) U(nnecessary), if the symptom s_j is indifferent for diagnosing the disease d_i in its p_{ki} description. In that way only the symptoms whose presence or absence is discriminant are considered.

An elementary sample of a MKB is represented in Fig. 2. After having constructed the medical knowledge base, we have now to describe the sequential decision making problem.

In the model we are proposing the problem of constructing a diagnosis through a sequential method is formalised using the state-space approach of problem solving (Nilsson, 1971).

The state-space representation requires the identification of all the possible situations of the problem (the state-space) and of the operations that change one situation into another (the operators).
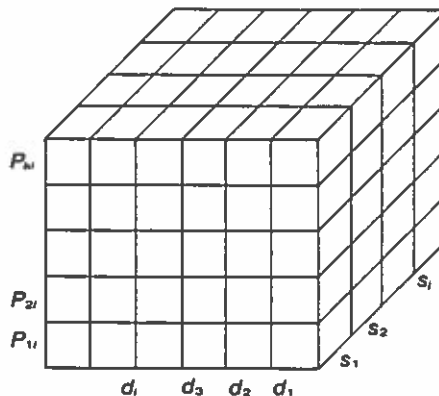

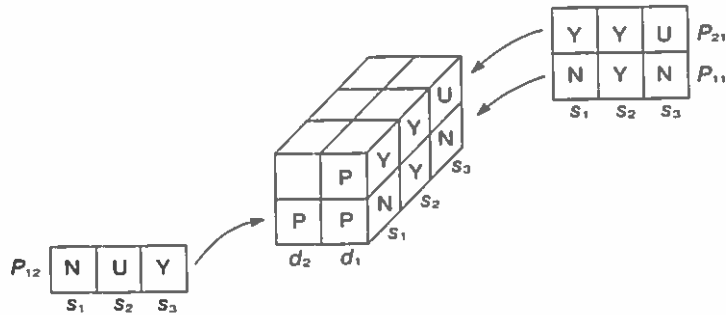
Fig. 1. Array expressing the medical knowledge.

Fig. 2. Sample of medical knowledge base.

A situation of the problem corresponds to an element st called state. Each state can be viewed as representing all the diseases consistent with the experimental data obtained at a given moment during the testing process.

A *state st* is an M-ple of ordered pairs (s_j, v_j) where M is the total number of symptoms. The value v_j obtained by the test t_j associated with the jth symptom can be

(a) 0 if the symptom s_j has not yet been tested;
(b) 1 if the symptom s_j has been tested and it is present;
(c) -1 if the symptom s_j has been tested and it is not present.

The set ST of the states is the *state-space*.

The initial situation is represented by a particular state st-i, called initial state. It corresponds to the situation in which no tests have been performed on the patient.

The *initial state st-i* is a M-ple of ordered pairs (s_j, v_j) where $v_j = 0$ for $j = 1, \ldots, M$.

The final situations correspond to particular states, the final states. They are characterised by the fact that they match a particular disease description p_{ki} in the sense that:

(a) the value 1 is associated to the symptom s_j if $MKB(i, j, k) = Y$;
(b) the value -1 is associated to the symptom s_j if $MKB(i, j, k) = N$;
(c) any of the three values 0, 1 or -1 is associated to the symptom s_j if $MKB(i, j, k) = U$.

The *set of final states with respect to the disease* d_i is the set of states corresponding to the elements of P_i in the sense described below. The *set of final states* is the union set of all the final states with respect to the different elements d_i of D, namely is the set of the states corresponding to all the elements of MKB.

A *final state* st-f_{ki}, corresponding to the kth description of the disease d_i, is a M-ple of ordered pairs (s_j, v_j) where

(a) $v_j = 1$ if the symptom s_j must be present;
(b) $v_j = -1$ if the symptom s_j must not be present;
(c) $v_j = 0$ or 1 or -1 if the symptom s_j is indifferent.

The set of operations that change a situation into another corresponds to a *set of operators* that change a state into a new state. An operator has the meaning of measure operator. Its application is equivalent to the execution of the test associated to the symptom. Thus, to each symptom s_j is associated an operator g_j, which can be applied only to the states st' characterised by the presence of the value $v_j = 0$ in the couple (s_j, v_j).

An *operator* g_j is a function which corresponds to the application of the test t_j to the symptom s_j and which assigns the value v_j according to the result of the test. The new state st'' obtained is the same as the previous state st', with the only exception of the couple (s_j, v_j) in which the value of v_j is changed.

A graph model can be used to describe the representation, in which a vertex corresponds to a state and an arc directed from one vertex to another corresponds to an operator.

The state-space for the small example illustrated before is represented in Fig. 3.

IV. ACQUISITION OF TEST OUTCOMES

The problem we have to solve is the determination of a diagnosis on the basis of the symptoms presented by the patient. What makes the problem hard is a combination of different factors, related to the difficulty of extracting significant information from the noise of less relevant clinical signs, as well as to the lack of sensitive discriminants between diseases with similar manifestations and to
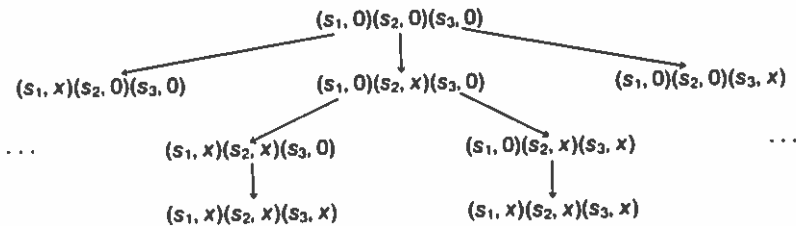
Fig. 3. State-space representation.

the hardness in understanding and reproducing the physician reasoning process.

What we propose is a consultation system, intended to assist the physician during the determination of the sequence of diagnostic tests to perform on the patient.

We start with the restrictive hypothesis that the patient has one and only one of the diseases of the considered set and so we are sure that a solution of the problem exists. What we want to explore is the road required to obtain the solution, with the aim of minimising the discomfort of the patient by minimising the number of diagnostic tests.

In the state-space approach the *solution* of a problem is a sequence of operators such that their successive application to the initial state produces a final state.

If the graph model is considered a solution is a directed path from the initial to a final vertex. Then the search of the solution is reduced to the search of a path between two vertices in a directed graph.

The use of the state-space formalism allows to apply all the well known algorithms for the search of the solution in a graph (Nilsson, 1971). However a general solution method becomes very time consuming and, definitively, inadequate for our purposes. In this case we have to resort to heuristic solution methods that yield more appropriate solutions.

The method we propose is based on the idea of ordering in a dynamic way the available operators. It allows the application of the most promising operator firstly and the generation of one successor vertex at a time, so allowing the implementation of a sequential diagnostic process. In the evaluation of the most promising operator both the theoretical medical knowledge, expressed in the MKB, and the practical experience with the patient, expressed through the results of the performed tests, are introduced. The problem of determining the sequence of tests is related to the problem of computing the most promising operator, where the promise of an operator is something related to its discrimination power in the particular situation. In fact some tests may be quite well suited for separating the members of a specific subset of diseases, and so performing those tests makes sense only where the probability of presence of that subset is sufficiently high, while other tests are suitable to separate different groups of diseases.

The algorithm we developed is a traditional search algorithm used for problem solving, in which the next node to expand at each step is computed through a special scoring algorithm, based on the determination on the promise of the available operators. The outline of the developed algorithm is illustrated in Fig. 4. Note that the algorithm works on the MKB and on the knowledge about the patient situation, since each time the scoring module operates on the individual knowledge base. We will examine how the promise is defined and
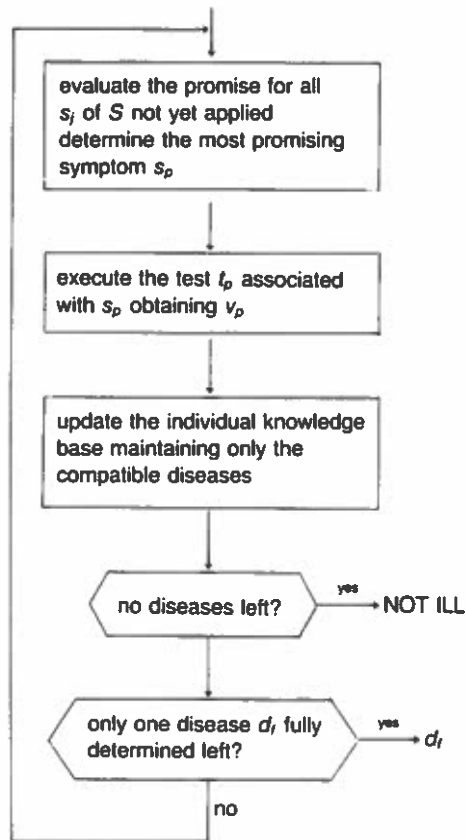
Fig. 4. The search algorithm.

computed. Before that it is important to notice that the scoring module is completely independent and it may be changed without affecting the rest of the program; so the scoring procedure may be changed according to particular classes of diseases or different requirements.

The *promise* for the test associated with the symptom s_j to diagnose the disease d_i is given by the sum of two terms related both to the discrimination power of the symptom and to the cost of the associated test. The cost is a number which takes into account the real cost, the risk for the patient and anything else that has to be minimised

$$\text{Promise}(s_j, d_i) = \frac{1}{c_j} * \frac{1}{h_i} * \sum_{k=1}^{h_i} (\text{if MKB}(i, j, k) = Y \text{ then } 1)$$
$$+ \sum_{k=1}^{h_i} \quad (\text{if MKB}(i, j, k) = N \text{ then } 1)$$

where the only reason for separating the two terms lies in the idea of preferring to test a symptom that is likely to be present in the case in which different operators came out to have the same promise. The variable h_i indicates the number of different relations describing the disease d_i, and it is used to normalise the scores.

The promise for the test associated with the symptom s_j is given by the sum of the promises for each disease

$$\text{Promise}(s_j) = \sum_{i=1}^{N} \text{Promise}(s_j, d_i)$$

After the application of the selected operator, the individual knowledge base is updated to eliminate the diseases not consistent with the observed test outcome. In fact whenever the symbol Y(es) is in the knowledge base in the position (i, j, k) and the symptom is not present ($v_j = -1$) or the symbol N(o) is in (i, j, k) and the symptom is present ($v_j = 1$), the corresponding element p_{ki} is no longer compatible with the individual state of the patient.

The patient may result as NOT ILL, if none of the diseases is compatible with his state, or his disease d_f can be found. In that case d_f is the only remaining disease fully determined; the assumption 4 guarantees that there is no possibility of having more than one disease with the same symptoms.

The small example illustrated before produces the solution presented in Fig. 5, where the costs are considered equal to 1.

V. SEQUENTIAL DIAGNOSIS OF ARTHRITIS

The algorithms described earlier have been programmed and tested on a computer. To exercise the system on a real life case the differential diagnosis of arthritis was considered. The group of diseases defined in the MKB is composed by 7 elements; possibly 22 symptoms deserve consideration to gather information about the patient. The MKB used is linearised in Table 3. The
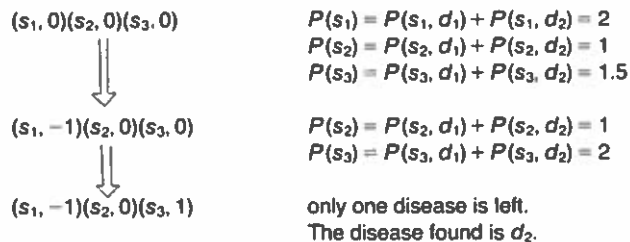
$$(s_1, 0)(s_2, 0)(s_3, 0)$$

$P(s_1) = P(s_1, d_1) + P(s_1, d_2) = 2$
$P(s_2) = P(s_2, d_1) + P(s_2, d_2) = 1$
$P(s_3) = P(s_3, d_1) + P(s_3, d_2) = 1.5$

⇓

$$(s_1, -1)(s_2, 0)(s_3, 0)$$

$P(s_2) = P(s_2, d_1) + P(s_2, d_2) = 1$
$P(s_3) = P(s_3, d_1) + P(s_3, d_2) = 2$

⇓

$$(s_1, -1)(s_2, 0)(s_3, 1)$$

only one disease is left.
The disease found is d_2.

Fig. 5. Search of the solution.

TABLE 3
SMALL PORTION OF THE MKB FOR ARTHRITIS

	arthritis	attacks	tophi	uricemia	chondrocal	calcium_cr	t_spine	l_spine	chest_decr	sacroiliac	chronic	polyarthr	symmetric	p_interph	rheumatoid	nodules	metacarpo	wrists	d_interph	knees	xrayeroded	synovial
gout	Y	Y	Y	U	U	U	U	U	U	U	U	U	U	U	U	U	U	U	U	U	U	U
	Y	Y	N	Y	U	U	U	U	U	U	U	U	U	U	U	U	U	U	U	U	U	U
pseudogout	Y	Y	N	N	Y	Y	U	U	U	U	U	U	U	U	U	U	U	U	U	U	U	U
prob_pseudogout	Y	Y	N	N	Y	N	U	U	U	U	U	U	U	U	U	U	U	U	U	U	U	U
	Y	Y	N	N	N	Y	U	U	U	U	U	U	U	U	U	U	U	U	U	U	U	U
ank_spondylitis	Y	Y	N	N	N	N	Y	U	Y	U	U	U	U	U	U	U	U	U	U	U	U	U
	Y	Y	N	N	N	N	Y	U	N	U	U	U	U	U	U	U	U	U	U	U	U	U
	Y	Y	N	N	N	N	N	Y	Y	U	U	U	U	U	U	U	U	U	U	U	U	U
	Y	Y	N	N	N	N	N	Y	N	Y	U	U	U	U	U	U	U	U	U	U	U	U
	Y	N	U	U	U	U	Y	U	Y	U	U	U	U	U	U	U	U	U	U	U	U	U
	Y	N	U	U	U	U	Y	U	N	Y	U	U	U	U	U	U	U	U	U	U	U	U
	Y	N	U	U	U	U	N	Y	Y	U	U	U	U	U	U	U	U	U	U	U	U	U
	Y	N	U	U	U	U	N	Y	N	Y	U	U	U	U	U	U	U	U	U	U	U	U
poss_ank_spondylitis	Y	Y	N	N	N	N	Y	U	N	N	U	U	U	U	U	U	U	U	U	U	U	U
	Y	Y	N	N	N	N	N	Y	N	N	U	U	U	U	U	U	U	U	U	U	U	U
	Y	N	U	U	U	U	Y	U	N	N	U	U	U	U	U	U	U	U	U	U	U	U
	Y	N	U	U	U	U	N	Y	N	N	U	U	U	U	U	U	U	U	U	U	U	U

system allows an easy interaction with the physician; at each step a question is posed, the question which promises to be the most informative at the given moment. The demand for a system capable of handling an interactive dialogue required human engineering features, designed to make interactions simple. Another important point was the need to design a system to accommodate a large and changing body of technical knowledge. Our choice of the model was significantly influenced by such features of the knowledge base. A sample of a dialogue is illustrated in Table 4.

VI. CONCLUSIONS

We have shown that the medical diagnosis problem can be formulated as a problem in the state-space approach to problem solving. We have proposed an algorithm for the search of the solution which allows a considerable reduction of the number of symptoms that have to be tested for obtaining a diagnosis. The encouraging results reported suggest the usefulness of sequential methods for computer assisted differential diagnosis. The operations involved are relatively simple; however, the use of the computer allows a natural and easy dialogue with the physician and gives directly the most suitable order for tests, minimising errors and increasing speed.

TABLE 4
EXAMPLE OF DIALOGUE

*** assign patient identification = pd143

is arthritis present? yes
is attacks present? yes
is tophi present? no
is hyperuricemia present? no
is chondrocalcinosis present? yes
is calcium_crystals present? no

———→diagnosis of pd143 is probable_pseudogout

*** assign patient identification = lj641

is arthritis present? yes
is attacks present? no
is t_spine present? yes
is chest_expansion_decreased present? no
is sacro_iliac_joints present? yes

———→ diagnosis of lj641 is ankylosing_spondylitis

*** assign patient identification = mn431

is arthritis present? yes
is attacks present? no
is t_spine present? no
is l_spine present? no
is chronic present? yes
is polyarthritis present? yes
is symmetrical present? no
is rheumatoid_factor present? yes
is nodules present? yes
is pip_involved present? yes

———→diagnosis mn431 is classic_rheumatoid_arth

*** assign patient identification = fr563

is arthritis present? yes
is attacks present? no
is t_spine present? no
is l_spine present? no
is chronic present? yes
is polyarthritis present? yes
is symmetrical present? yes
is pip_involved present? no
is mcp_involved present? no
is wrists_involved present? yes
is rheumatoid_factor present? no
is x_ray_erosions present? yes
is dip_involved present? yes

———→ diagnosis of fr563 is erosive_osteoarthritis

The class of diseases among which the diagnosis is performed has to be defined initially in the medical knowledge base. However, it is possible to modify that table, by adding new definitions or new symptoms, without changing the program that is table-driven.

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