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AI/LEARN Network

The Use of Computer-Generated Graphics to Augment the Educational Utility of a Knowledge-Based Diagnostic System (AI/RHEUM)

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AI/LEARN Network is an educational package that enhances a knowledge-based diagnostic system called AI/RHEUM. This paper describes a microcomputer-based graphical representation of the knowledge base and discusses graphical representation of knowledge.

INTRODUCTION

Traditionally, knowledge-based medical diagnostic systems employ linguistic user interfaces. Some recent systems offer visual representations, not merely for their superficial appeal but to improve the understanding and use of the knowledge base. Graphics have been used to enhance data entry for the ONCOCIN system.[1] OPAL, a graphical knowledge acquisition system for ONCOCIN, uses both iconic and form representations.[2] William G. Cole argues that "cognitive graphics" reduces "cognitive strain" and helps people to reason about diagnosis.[3] This paper describes a prototypical system that uses graphics to augment a knowledge-based rheumatologic diagnostic system called AI/RHEUM[4,5] and explains how issues of knowledge representation are involved in the system design.

AI/RHEUM, a knowledge-based computer consultant system for the diagnosis of rheumatic diseases, was developed using system-building software called EXPERT.[6] The current knowledge base includes tables of diagnostic criteria for 26 rheumatic diseases. The criteria tables, which represent the knowledge used in the AI/RHEUM reasoning process, were developed at the University of Missouri-Columbia and reviewed by rheu-

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matology consultants. The tables contain combinations of major and minor decision elements, required elements, and exclusions, all of which lead the system to diagnostic conclusions. An example of the criteria table for systemic lupus erythematosus is shown in Table 1.

Table 1. Proposed Criteria for Systemic Lupus Erythematosus[a]

Major criteria	Minor criteria
1. Nephritis	1. Fever
2. Serious central nervous system disease	2. Arthritis, oligoarticular OR polyarticular
3. Pleuritis, OR pericarditis	3. Alopecia
4. Malar rash	4. Photosensitivity
5. Autoimmune hemolytic anemia	5. Mucosal ulcerations
	6. Hypergammaglobulinemia, > = 1.8 gm%
	7. Hypocomplementemia
	8. Thrombocytopenia < 100000/cmm OR leukopenia < 3500/cmm
	9. Discoid lupus erythematosus
	10. False positive VDRL or RPR
	11. Raynaud's phenomenon
	12. Circulating anticoagulant
	13. Lupus band test positive

Clinical combinations of findings		
Definite	Probable	Possible
A. 4 majors	A. 1 major 3 minors	A. 3 minors
B. 3 majors including #1 or #2 2 minors	B. 4 minors	B. 1 major 2 minors
C. 2 majors including #1 or #2 4 minors	C. 2 majors 2 minors	
D. 3 majors including #1 and #2		
Required findings		
ANA + OR LE cell + OR anti-Sm + OR anti-DNA +	ANA + OR LE cell + OR anti-Sm + OR anti-DNA +	No requirements
Exclusionary findings		
Sclerodactyly Arthritis, erosive anti-RNP +, with ENA > = 1:10,000 AND with anti-Sm −	Same	None

[a] The Criteria Table consists of lists of major and minor features of the disease, required and exclusionary findings, and the logical combinations of the findings leading to conclusions of the disease with varying certainties.

The AI/RHEUM reasoning process leads from patient findings, to intermediate hypotheses (logical combinations of patient findings), and then to diagnostic conclusions (logical combinations of patient findings and intermediate hypotheses). The strength of confidence in the conclusions are listed as definite, probable, or possible and are presented as differential diagnoses. For each differential diagnosis, the system lists those findings that support the conclusion, those which are currently unknown but which, if known and positive, would tend to strengthen the conclusion, and those findings which are true but which are *not* normally expected with that diagnosis. Listing the unexpected findings alerts the user to consider the possibility of other diseases. Table 2 illustrates a typical output from AI/RHEUM.

AI/RHEUM can understand, store, and reason from 877 observations (findings) for each patient. Patient findings are entered in terms of positive, negative, unknown, and numeric values. The system will reason from whatever information is given and can reach correct diagnostic conclusions from only a handful of observations, if those observations are important indicators. It will also signal when there is insufficient information to reach a diagnosis.

The usefulness of AI/RHEUM as a means of enhancing the learning of rheumatology and related diagnostic skills has been studied at the University of Missouri since 1983.[7–9] A computer program has been developed that allows the use of paired photographic images to enhance observational skills in basic clinical concepts in rheumatology,[10,11] and the same program is used to present case simulations to train users in problem-solving skills. A second series of programs presents a graphical representation of a knowledge base, allowing interactive exploration by the user. This series of programs is the subject of the present paper.

MATERIALS AND METHODS

Hardware

AI/LEARN Network runs on the IBM PC AT microcomputer with 640K RAM, an Enhanced Color Adaptor with 256K RAM driving an Enhanced Color Display, and a Microsoft Mouse. Similar equipment can be used to run AI/RHEUM.

Software

The interaction programs have been written with a combination of PROLOG, C and assembler languages. This multilingual approach provides power and efficiency.

Prolog is one of several computer languages commonly used in artificial intelligence research, and in the AI/LEARN Network programs it is used to manipulate the deductive database, to perform representation translation, and for text manipulation. Turbo-PROLOG (Borland International) was used to create and manipulate a database of nodes and links that store the representation of the knowledge base in AI/RHEUM. The built-in inference power of PROLOG allows easy translation from lexical to graphical forms while the screen windowing and editing capabilities were used to present explanatory text derived from the Tell-Me-Mores (TMMs) of AI/RHEUM.

Table 2. AI-RHEUM Interpretive Diagnosis for Case 120[a]

Name: 26-73-74-6—01-20-26
Case: 120, Visit: 1, Date: 01/30/78
Diagnoses are considered in the categories: definite, probable, possible.
Based on the information provided the differential diagnosis is
Systemic lupus erythematosus —Probable
Polymyositis —Possible
The diagnosis of Systemic Lupus Erythematosus is supported by the patient findings:
Malar (butterfly) rash
Alopecia
Photosensitivity
Oral/nasal mucosal ulcers
Hypocomplementemia
Thrombocytopenia or leukopenia
Skin biopsy, lupus band test positive
ANA +, titer 1:>1:40
LE cells
These findings are NOT explained by the diagnosis Systemic Lupus Erythematosus:
Serum glucose, mg% 125
The following findings, currently unknown would, if known, tend to strengthen the conclusion of Systemic Lupus Erythematosus:
Platelet count, /cu mm <100,000
Gamma globulin, gm%
Creatinine clearance, ml/min
Renal biopsy, membranous glomerulonephritis
Renal biopsy, diffuse glomerulonephritis
Renal biopsy, mesangial glomerulonephritis
Renal biopsy, focal glomerulonephritis
The diagnosis of Polymyositis is supported by the patient findings:
Proximal muscle weakness, mild
Abnormal muscle biopsy, mild
These findings are NOT explained by the diagnosis Polymyositis:
Alopecia
Skin biopsy abnormal
Skin biopsy, lupus band test positive
Oral/nasal mucosal ulcers
Other pulmonary abnormality
Other cardiac abnormality
Other GI abnormality
Lymphadenopathy
WBC count, /cu mm 3300
LE cells
Serum glucose, mg%125
C4 complement, patient value 10 —End of consultation—

[a] The interpretive analysis from AI/RHEUM stems from the reasoning process described in the text.

The PROLOG main program calls C functions to control the mouse and display high-resolution color graphics. C is well suited to these functions, and the existence of commercially available comprehensive C graphics libraries is an added bonus. Using these libraries has allowed implementation of advanced graphical features such as page buffering—displaying one screen page while updating the other "hidden" page.

Certain time-critical sections were written in assembly language to improve the response time. This is mainly due to performance considerations; these sections could have been implemented in C.

RESULTS

The method of graphical representation used is intuitive and simple and can be implemented on a microcomputer. Two-dimensional inference network graphs have been used previously for the representation of rules in a knowledge base.[12] The addition of interaction allows the user to develop an understanding of the knowledge base in small self-directed steps.

A single node is displayed in the center of the screen, linked to nodes on the left and right. The nodes are represented by colored boxes linked, by labeled lines, to other nodes in the display. The deductive reasoning works from left to right: The nodes in the left column are used in the deduction of the central node, which, in turn, is used with other nodes in the deduction of the right column. The central node may represent a pathophysiological state; for example, the leftmost nodes are the observable findings, while the rightmost is the differential diagnosis. If there are more left or right nodes than can be displayed on one screen, they can be scrolled into view. Users traverse the graph by using the mouse; "clicking" on any node brings that node into the central location (see Figure 1). By changing into the query mode, one can obtain a more detailed description of any displayed node (see Table 3). This description may consist of AI/RHEUM's TMMs (Tell Me More) or a disease diagnostic criteria table.

The background color of each node shows its type, i.e., history, physical sign, laboratory results, invasive investigation, intermediate hypothesis, differential diagnosis. The user can select the order in which the nodes appear in the left or the right column. The ordering available is "history-examination-laboratory," decreasing "evoking strength," or decreasing "frequency of association."[13] The relative evoking strength can be illustrated by the thickness of the link. The evoking strength and frequency of association are features that, while not implemented in AI/RHEUM, have been included in AI/LEARN Network to incorporate rules with varying confidence factors,[14] as well as to make the system immediately applicable to other medical domains (e.g., QMR).[15]

Disease- and patient-specific graphs can be constructed. In a disease-specific graph, the nodes and links related to a specific disease and its definitions are shown. In the patient-specific model, only those nodes and links that are applicable to a particular patient (in the sense of positive or relevant negative findings and intermediate hypotheses) are illustrated. Figure 2 shows the patient-specific graph produced by AI/LEARN Network for the AI/RHEUM case 120 shown in Table 2.

DISCUSSION

Initial experience with these prototypes has confirmed that medical students and experienced rheumatologists can easily grasp the information on associations between findings, hypotheses, and disease as displayed by AI/LEARN Network system. Allowing

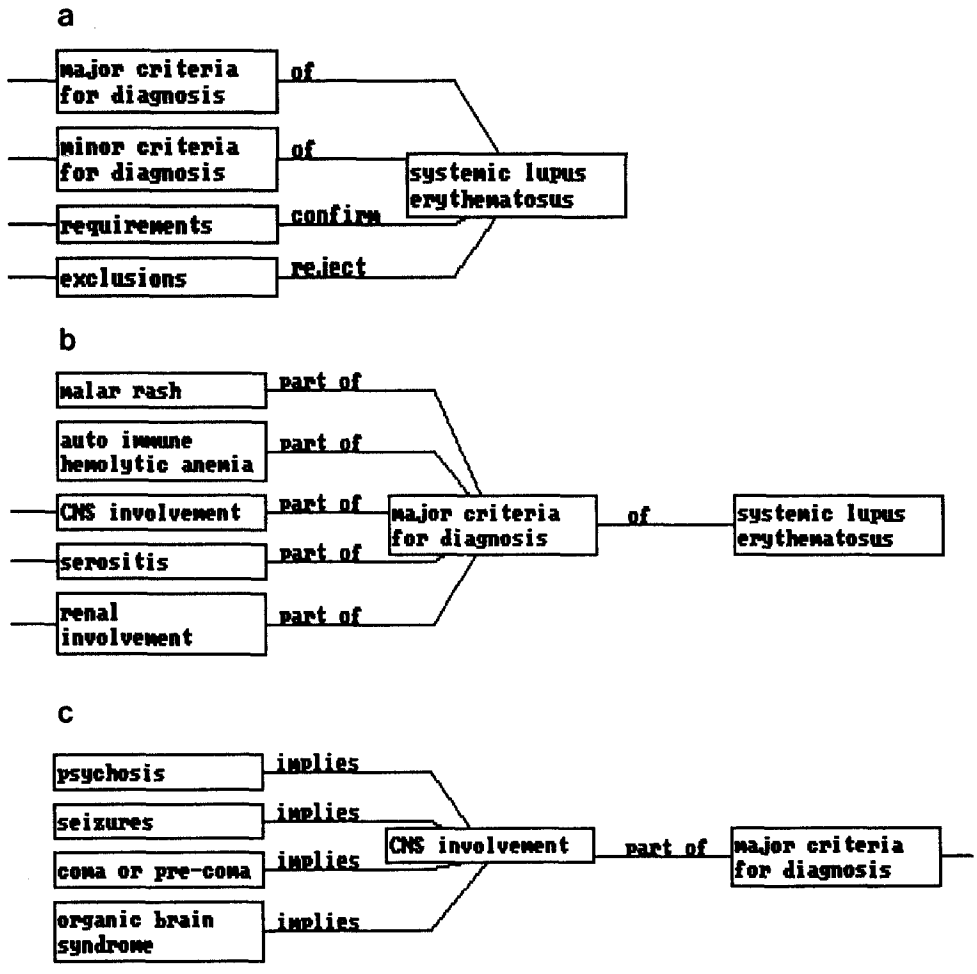

Figure 1. Topic-specific model. The interrelationships among symptoms, signs, laboratory results, and intermediate hypotheses leading to the diagnosis of systemic lupus erythematosus (SLE) are illustrated. The user can traverse the graph, for example, by positioning the cursor on "major criteria for diagnosis" and depressing a button on the mouse device (a). "Major criteria for diagnosis" will appear in the center of the next screen (b). Similarly, selecting "CNS involvement" will reveal more details (c). CNS involvement is an intermediate hypothesis in AI/RHEUM and not a terminal node.

active exploration of the network of associations provides intellectual challenge that stimulates cognitive learning.

Different schemes for representing knowledge require different graphical presentations. In some cases, the knowledge representation itself is an abstraction of a graph (e.g., CASNET's causal-associational network).[16] Therefore, the knowledge base can be illustrated simply by a two-dimensional directed graph, with text "boxes" for nodes and with lines showing the links.

The graphical illustration of other features in knowledge representations is far from trivial. Consider, for example, the multiple levels of detail of ABEL,[17] and "non-graphical" representations such as frames/predicate or logic/patterns. Even in AI/

Table 3. Query Mode Definitions

What: Psychosis.
Psychosis: a loss of contact with reality, a thought disorder, or a change of personality or behavior often associated with delusions, illusions, or hallucinations.
Why:
Psychosis may occur in systemic lupus erythematosus, in mixed connective tissue disease, or with the administration of steroids, cimetadine (Tagemet), or reserpine.
How:
A psychosis probably exists if a patient demonstrates one or more of the following major criteria:
Major criteria
Loss of contact with Reality—evidenced by the misinterpretation of the environment as hostile when friendly or vice versa, generally causing bizarre responses to normal and usual environmental stimuli
Thought disturbance—evidenced by incoherence, marked illogical content, marked loose associations, or patient's admission of mental confusion and abnormal rate of mental activity
Personality/behavior changes—characterized by rapid onset and reversals of previous behavior patterns, often observed by reliable family member or friend
The diagnosis if further strengthened by the presence of one or more of the following minor criteria:
Minor criteria
Delusions—firmly held beliefs that cannot be dissuaded by logical discussion, generally of a threatening, powerful, or grandiose nature
Illusions—misperceptions of environmental stimuli, e.g., perceiving a person instead of an actual tree shadow
Hallucinations—perceptions without environmental stimuli, e.g., hearing voices/noises or seeing a face/vision
Refs:
Differential diagnosis of psychotic features. *Diagnostic and Statistical Manual of Mental Disorders,* 3rd ed. (DSM III). American Psychiatric Association, Washington, D.C.: 1980. MH: Mental Disorders/*CL/classification; Psychiatry/*/nomenclature. UI; 8007814.
Rothfield, N., Clinical features of systemic lupus erythematosus. *Textbook of Rheumatology* (W. N. Kelley), W.B. Saunders, Philadelphia, MH: Arthritis/*// Rheumatism/*//. UI: 8000657.
Bennett, R. M., Bong, D. M., and Spargo, B. H., Neuropsychiatric problems in mixed connective tissue disease. *Am. J. Med* 65(6):955–962. 1978 MH: Adrenal Cortex Hormones/THERAPEUTIC USE; Adult; Case Report; Cerebellar Ataxia/*ETIOLOGY; Convulsions/*ETIOLOGY; Female; Human; Meningitis/*ETIOLOGY; Meningitis, Aseptic/DRUG THERAPY/ *ETIOLOGY; Middle Age; Mixed Connective Tissue Disease/ *COMPLICATIONS/PSYCHOLOGY; Peripheral Nerve Diseases/*ETIOLOGY; Psychotic Disorders/*ETIOLOGY. UI: 79121960. DN19307-1.
Steinberg, A. D., Management of systemic lupus erythematosus. William N. *Textbook of Rheumatology* (W. N. Kelley), W.B. Saunders, Philadelphia, 1981, Chap. 70. MH: Arthritis/*// Rheumatism/*//. UI; 8000657.

[a] By changing into the query mode, selecting any node on screen brings up the full definition of it in the same format as the "Tell-Me-More" feature of AI/RHEUM (4). Here the definition of the term "Psychosis" is shown.

RHEUM, which uses a refinement of CASNET's approach, significant problems remain unsolved. In patients with multiple differential diagnoses, there are two ways of constructing the graphical representation. Either all the differential diagnoses and related findings can be shown in one graph, or several graphs can be constructed, each of which represents one diagnosis. The current system is designed to illustrate a single diagnosis.

Another problem is the accurate inclusion of combinatorial rules in the graphical representation. A rule in AI/RHEUM is of the general form

$$[n\text{: } P1(L1{:}H1),\ P2(L2{:}H2),\ P3(L3{:}H3),\ \ldots\ Pm(Lm{:}Hm)] \rightarrow C(cf)$$

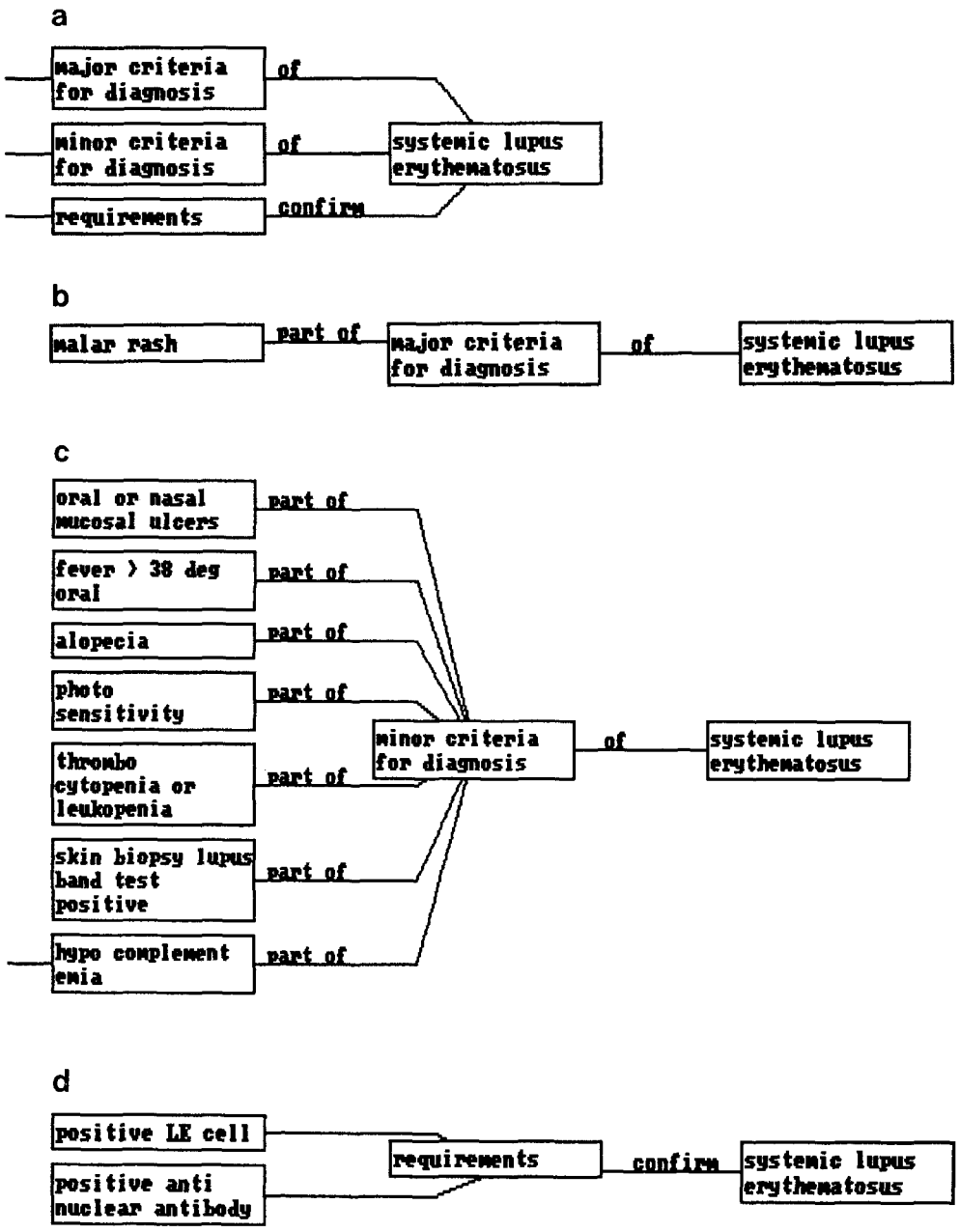

Figure 2. Patient-specific model. This graph (a) complements the textual interpretive diagnosis for Case 120 (Table 2). The major criteria (b), minor criteria (c), and confirmary tests (d) related to this patient are illustrated.

(syntax slightly simplified for ease of explanation)

This says that there are *m* premises. A premise holds if the observed (or inferred) confidence factor lies within the low and high limits (e.g., *L2 and H2*, respectively, for

premise $P2$). If at least n of the m premises hold, then one can reach the conclusion C with a confidence of cf.

The representation, as implemented, decomposes such a rule into several one-to-one relationships between a premise and its conclusion (i.e., $P1 \rightarrow C$, $P2 \rightarrow C$, etc.). None of the quantitative information (i.e., n, m, and the confidence limits) are shown. Included in the system is the ability to display the relative importance among the premises in terms of the evoking strength. This is done by increasing the thickness of the link to nodes with greater evoking strength. Another way of showing relative evoking strength is provided by the ability to order the nodes from the greatest evoking strength to the least.

In the prototype system, the PROLOG databases storing patient-specific graphs are created by manual examination of the AI/RHEUM output. The next logical step would be for AI/RHEUM to produce these databases. This would allow the use of the AI/LEARN Network displays to clarify the diagnostic logic used in AI/RHEUM.

Further development of the system could allow interactive modification of the inference network graphs. By "customizing" the knowledge base the advanced user could test the effects of the modifications on the outcome of the network. This represents an improved system for adding new knowledge/diagnoses to AI/RHEUM since visual inspection of the model could be performed before implementing the disease update.

Three-dimensional graphs may be the best representation of multilevel descriptions of knowledge. However, owing to the tremendous computational power required, three-dimensional representations have not been attempted. It may become feasible to pursue this form of representation when graphics processor boards become available.

CONCLUSION

A prototype graphics representation of inference logic has been developed to be used as an adjunct to a microcomputer knowledge-based diagnostic system. Augmenting the educational utility of the knowledge-based system enhances acceptability and use of the diagnostic system by the medical and computer science communities.

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