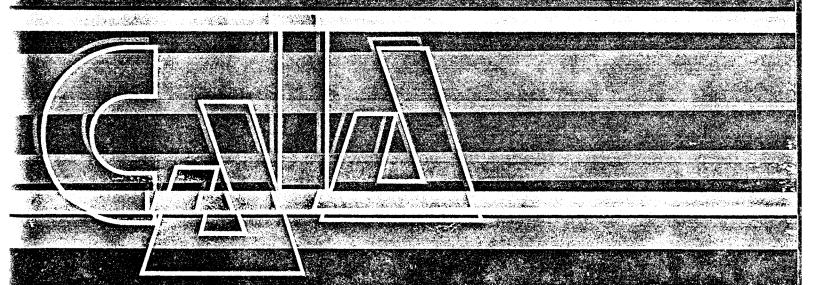
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Analogical and Propositional Representations of Structure in Neurological Diagnosis*

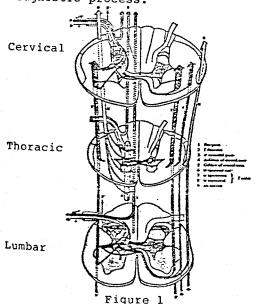
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Abstract

The issue of representation of 3-d neurological anatomic structure in the design of an expert system for localizneurological lesions is discussed. direct analogical representation that consists of a series detailed cross-sectional drawings of the central nervous system, and a propositional representation that represents structure by spatial relations and function by reasoning rules is discussed.

I. Introduction

The central task of neurological diagnosis involves the use of anatomic models of the intricate 3-d structure of the central nervous system (CNS), i.e., spinal cord and brain, and the peripheral nervous system (PNS). An example of the structure of tracts within the spinal cord is shown in Fig.l. Spatial knowledge representation and reasoning is a crucial part of anatomic localization which is the crux of the whole diagnostic process.



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The effort of our research group is directed towards building a system for computer consultation in neurological

diagnosis. A prototype NEUROLOGIST-I, written in Franzlisp runs on a VAX-11/750 (using DEC-GIGI graphics) at Buffalo. The domain NEUROLOGIST-I is the CNS; its structural knowledge is purely <u>analogical</u>, i.e. geometrical, and its reasoning is similar to that of an earlier (Fortranbased) system of Catanzarite[2]. NEUROLOGIST-II, under development, uses an <u>analogical/propositional</u> representation of structure; it uses a multiplelevel representation with more detail in the CNS than NEUROLOGIST-I and includes portions of the PNS. In this paper we discuss representation of CNS structure in NEUROLOGIST-I and NEUROLOGIST-II.

II. Neurological Diagnosis

Five major steps in the process of neurological diagnosis can be formalized as follows:

- 1) Patient Data Collection. Preliminary patient data including the neurologic complaints and their time related historical data and the results of a physical examination are typically documented by clinicians using forms and pictorial drawings to indicate the extent of anatomy affected. NEUROLOGIST-II, patient data are collected in two different forms, text and graphical. An example in Fig.2 shows a menu and the lateral view of the head showing the distribution of cutaneous nerves to head and neck. The latter is used to indicate sensory abnormality.
- 2) Localization. Neurologic lesions accounting for the patterns of neurologic symptoms and findings elicited by the first step are localized using two phases. First, neurologic findings are mapped into nervous tract status (as normal, abnormal, etc.) for each longitudinal nervous system. Next, localization is attempted. Neurologic lesions can be divided into two classes. Anatomic lesions are discrete, spatially continuous disruptions of neuroanatomic structures, as might be caused by a

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bullet or a tumor. Non-anatomic lesions are patterns of malfunction which do not correspond to spatially continuous regions of the nervous system, but are caused by biochemical or physiological disturbances, e.g., malfunction of the sensory fibers serving vibration sensation is seen in diabetic neuropathy. Localization involves the use of a model of the human nervous system. The model consists of both structure, which tells the location of a particular nervous tract and its relative position with respect to other tracts, and function, which determines tracts that could be malfunctioning under given symptoms. Given the symptoms and physical examination results, the expert locates the possible lesion, points out whether the lesion is in the spinal cord or in the brain, which part of the spinal cord or the brain, especially, whether the lesion is in a spatially continuous form, e.g., a tumor, or in a noncontinuous pattern.

EYE AND ETE REVERENT EVAN

1. papilledona 2. wision (abnormal if no catracts Ebest correction (20) $\,$

- field cuts:
 3. inferior masal quadrant
 4. superior masal quadrant
 5. inferior temporal quadrant
 6. superior temporal quadran
- 7. direct pupillary light response 8. consensual light response

- extraocular concents:
 9. adduction
 10. down end in extion
 11. adduction
 12. attaic ngstageus on conjugate gaze to contralateral side

available commands: o - ok, n - next, s - skip, c - current, and a - previous

9. 41: In the left side which are definitely abnormal?

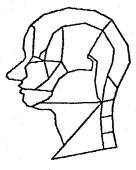


Figure 2

The first step in localization is to map the neurological findings into nervous tract status for each longitudinal nervous system. Tract status extrema are "normal" and "abnormal", with intermediate status being possible. An "unk-Examples nown" status is also allowed. of such mapping rules for cranial nerve are as follows where an integer representation from -10 to 0 to 10 is used to indicate tract status from "abnormal" to "unknown" to "normal", and different weights are assigned to determine the joint effect of several antecedents in a rule, each score can take value "-1" for abnormal, "0" for unknown or "1" for normal.

Rl. If atrophy with fasciculations of the tongue then lower motor neuron, hypoglossal nerve (XII) status:= score *

R2. If atrophy or weakness of the sternomastoid and atrophy or weakness of the trapezuis then upper motor neuron, spinal accessory nerve (XI) status:= scorel * 5 + score2 * 5.

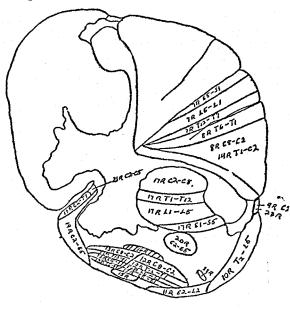
R3. If muscles of facial expression for the lower face are abnormal then upper opposite motor neuron, facial nerve (VII) status:= -10 and lower motor neuron, facial nerve (VII) status:= 10 * score (muscles of facial expression for the upper face).

- 3). Temporal Profile Construction. Each symptom has its own temporal profile to indicate the evolution of the symptom. The general profile is constructed by carefully combining the temporal profiles of each individual symptom.
- 4). Neuropathologic Differential Diagnosis. A set of neurologic diseases are selected for further consideration according to the result of localization and the general profile.
- 5). Hypothesis Evaluation. Once the differential diagnosis has been formed, each diagnostic possibility must be investigated. For this purpose, more patient data may be required, and specific tests might be ordered. Facts are used to confirm or detract the existence of each particular disease and also used as feedback to reconsider conclusions of previous steps.

III. An Analogical Representation

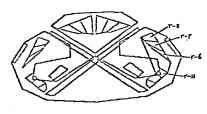
The 3-d structure of the CNS is analogically represented by line drawings of horizontal cross-sections in medical books, e.g., the cervical segment of the spinal cord is shown in Fig.3. Each labelled area represents a nervous tract carrying information upward or downward with the cross-section. Nervous tract cross-sections are approximated by polygons in several consecutive sections in NEUROLOGIST-I. The computer representation of each such cross-section is a set of vertex sets. Each vertex set contains a sequence of coordinate pairs for the vertices which can be linked by straight lines to form a polygon. Such cross sections are

shown in Figs.4 and 5. The principle used to judge whether the possible lesion is in a spatially continuous form is to compute a convex-hull, using a recursive divide-and-conquer algoinvolves all the which rithm[8], polygons formed by malfunctioning tracts for each cross-section. If a convex-hull involves or intersects more than one intact tract, the system will deny the possibility that a continuous lesion exists in that cross-section. Otherwise, the convex-hull will be considered a possible lesion. If a lesion is hypothesized in more than one level then either the lowest level is chosen or a multiple level lesion is hypothesized.



anatomic lesion inferred at level-5

Figure 3



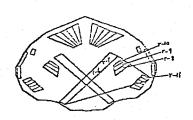
left right mid_cervical_cord

Figure 4

After entering patient data NEUROLOGIST-I displays a summary of malfunctioning tracts by mapping symptoms to tract status (Fig. 6). The single-level localization is to apply the convex-hull principle to each of 20 levels. If a possible lesion is found in a

level, the level will be scored according to the percentage of malfunctioning tracts which are involved in the lesion; otherwise, the level score is nil. Since possible lesions are found from level-1 to level-5 and combining the five lesions into a multiple level lesion can involve more malfunctioning tracts than the lesion in the lowest level, the system concludes a multiple-level lesion from level-1 to level-5. Fig.4 shows a consistent level with the corresponding convex-hull. Fig.5 shows an inconsistent level with the corresponding convex-hull.

inconsistent level-6



left right low-pyramid

Figure 5

Direct analogical representation has the following advantages: the structure of idealized anatomy can be precisely defined, the inference is guided by geometrical algorithms, and compatibility with graphics output devices is straightforward. There are several disadvantages:

- 1. It is usually an overspecification since the CNS is conceptually divided into tracts and there is no explicit boundary. Moreover, a tract may malfunction when it is partially affected by a lesion.
- 2. Anatomic knowledge is represented in a single low-level structure. The human cognitive approach seems to deal with abstract spatial relations rather than coordinates.
- 3. The knowledge structure is not oriented towards global reasoning. For example, if the system is to predict possible malfunctioning tracts for a given input, its structure should more directly support the searching of tracts surrounding the tracts concluded to be malfunctioning so far.

3-d structure Since the i s represented in the form of 2-d sections, it is not easy to do 3-d reasoning. A true 3-d oriented representation may be preferable, e.g., a hierarchical organization involving nested cubes [1], [10] supports 3-d reasoning and 3-d graphics display.

** Summary of Regular Examination**

Tracts with imperfect function:

r-6	corticospinal	score:	-10
r-7	corticospinal	score:	-10
r-8	corticospinal	score:	-9
r-9	corticospinal	score:	-9
r-11	spinothalamic	score:	-10

Single level localization results:

level-1	sacral cord	score: 40
level-2	lumbar_cord	score: 60
level-3	thoracic cord	score: 80
level-4	low cerv cord	score: 100
level-5	mid_cerv_cord	score: 100
levels 6-20		score: nil

Most consistent lesion location: level -1 to level -5 score: 100. Lesion explains malfunctions of corticospinal r-6-r-9 and spinothalamic r-11. Figure 6

IV. A Propositional Representation

A propositional representation has assertions that are true or false with respect to the model and are manipulated by rules of inference. The amount of detail of the structure that is present in the model depends on the antecedents of the inference rules and the conclusions we expect. Since the antecedent of anatomic localization is a set of nervous tracts which are totally or partially malfunctioning and the conclusion we need is the probability that one or more spatially continous lesion, e.g., a tumor, exists, the knowledge base needs to contain only the essential configuration of the nervous system. That is, each nervous tract can be treated as an entity and spatial relations can be described by primitives "next to", "right", "left", "above", "beneath", etc. The objective of NEUROLOGIST-II is to process inference rules based on such a representation scheme.

Consider a propositional representation system which has two spatial relations and five inference rules. Although neither the relations nor the

rules are limited to 2-d, we will use the cross-section of Fig.3 as an example. We can refer to each of the labeled areas as a nervous tract. We define two spatial relations between tracts as follows: adjacency- when two tracts have a common boundary they are adjacent to each other, and reachability- when it is possible to form a convex lesion which totally or partially affects two tracts totally or partially affects two tracts the two tracts are reachable from each Clearly, adjacency implies reachability. Thus the following are adjacent pairs: 17RC2-C8 and 17RT1-T12, 17RT1-T12 and 17RL1-L5, 17RL1-L5 and 17RT1-112 and 17RE1-E3, 17RE1-E3 and 17RS1-S5, 17RS1-S5 and 20RC2-S5, 16R and 13RC8-C2, 16R and 12RC8-C2, 13RC8-C2 and 12RC8-C2. The following are reachable pairs: 17RL1-L5 and 16R, 17RL1-L5 and 13RC8-C2, 17RS1-S5 and 16R, 20RC2-S5 and 16R, 20RC2-S5 and 16R, 20RC2-S5 and 12RC8-C2, 20RC2-S5 and 22R, 16R and 22R, 22R and 12RC8-C2. Five rules can be stated as follows:

rl. If a tract is known to be malfunctioning, check all adjacent tracts first and then the reachable tracts, e.g., if 16R (shown shaded in Fig. 3) is malfunctioning, then 13RC8-C2 and 12RC8-C2 might also be malfunctioning and therefore should be checked by an appropriate physical examination, and then 20RC2-S5, 17RS1-S5, 17RL1-L5 and 22R.

r2. If a set of malfunctioning tracts are adjacent to or reachable from each other, and there is no intact tract which is adjacent to or reachable from every tract in the set, we can conclude with a high degree of confidence that there is a convex lesion which affects all the malfunctioning tracts, e.g., if 16R, 20RC2-S5, 22R and 12RC8-C2 are malfunctioning then there might be a tumor which affects all of them. (Fig.7)

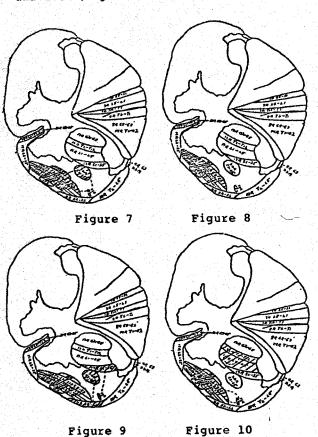
r3. If one can link all the malfunctioning tracts by adjacency relation then there probably exists a continuous lesion, e.g., if 13RS5-S1, 13RL5-L1, 13RT12-T1, 13RC8-C2 and 12RC8-C2 are malfunctioning, then there might be a continuous lesion which extends from 13RS5-S1 to 12RC8-C2. (Fig.8)

r4. If one can link all the malfunctioning tracts by adjacency or reachability relation, then a continuous lesion is possible. The confidence here is weaker than in r3, e.g., if 11RS2-L2, 22R, 20RC2-S5 and 17RS1-S5 are malfunctioning then a lesion can extend from 11RS2-L2 through 22R and 20RC2-S5 to 17RS1-S5. (Fig.9)

r5. If a set of malfunctioning tracts can be divided into two subsets such that no tract in one subset is adjacent

with the most confidence, if rule 2 does not apply but rule 3 applies (in this case, rule 4 also applies) then the system will consider a continuous lesion

to or reachable from a tract in the other subset, then we can consider multiple lesions, e.g., if 17RT-T12, 17RL1-L5, 12RC8-C2 and 22R are malfunctioning, then there might be one lesion which affects 17RT1-T12 and 17RL1-L5 and another lesion which affects 12RC8-C2 and 22R. (Fig. 10)



Note that NEUROLOGIST-I may derive incorrect conclusions in many cases. In the example for r2, a convex-hull involving the four malfunctioning tracts will intersect the intact tract 13RC8-In the example for r3, a convexhull involving the five malfunctioning tracts will intersect three intact ---12RT12-T1, 12RL5-L1 and 12RS5-S1. interestingly, NEUROLOGIST-I fails even in the example of the last section, where a conclusion is made that level-6, the low pyramids, is inconsistent since more than one intact tract is included in the convex-hull (fig. 5), however, it is obvious that we can form a convex totally or partially lesion which involves the five malfunctioning tracts and one and only one intact tract, r-10. include the confidence Rules r2-r4 degree to which the system believes that there is a convex and/or continuous lesion, e.g., given

malfunctioning tracts, if r2 applies (in this case, r3 and r4 also apply) then the system will conclude that there is a convex and continuous lesion which may or may not be convex with a fair confidence, if only r4 applies then the system will consider a continuous lesion with least confidence. If we let a polygon become a 3-d object, we can construct a model of the 3-d anatomy by a series of such thick plates put together closely. In this case, we need to generalize common boundaries to common surfaces and 2-d convex hulls to 3-d convex hulls.

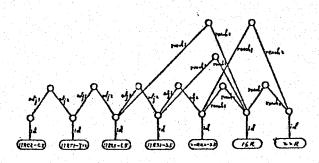


Figure 11

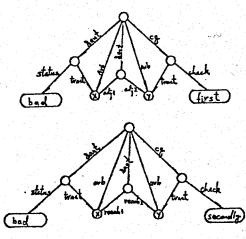


Figure 12

It is possible to implement the two relations and the five rules in a system which supports the representation of entities and their relations and logical inference such as SNePS, the semantic Network Processing System [9]. The high level knowledge about Fig.3 (only part of Fig.3 is shown) is built into a network representation (Fig.11). Inference rule rl is also built into the system (Fig.12). Given that tract 16R is malfunctioning, forward inference can be

triggered and the rule can be applied to derive the order in which tracts should be checked.

In fact, these rules can also be implemented by graph-theoretic algorithms. For example, if we consider each tract as a vertex and each adjacency or reachability relation as an edge between the two tracts, i.e., vertices, then the first antecedent of r2 is to verify a complete graph. In this case, the time complexity seems acceptable, e.g., to verify a complete graph, in the worst case, requires (n-1) + (n-2) + ... + 1 adjacency checks, i.e., O(n*n). Moreover, r3 is to verify the connectivity of the graph considering each adjacency relation as an edge, r4 is to verify the connectivity of the graph considering each adjacency as an edge.

V. Discussion

Several AI-based diagnosis systems have been developed previously including: MYCIN [4], a production rule based program to advise in the treatment of infections and INTERNIST [7], for general internal medicine. In most cases, separate factors, their relations and their effects are encoded into symbolic representation according to their semantics. No detailed knowledge of anatomic structure is used. An effective neurological consultation system needs to have access to both analogical and propositional anatomic representation of structure. A propositional representation is needed to support spatial reasoning -- inference rules can be stated and applied. An analogic or geometrical model of ideal anatomy is useful to provide a graphical explanation facility. Integration of both types of representation in a common knowledge-base leads to efficiency and consistency. The importance of reasoning based on representation of structure and function in electronic fault diagnosis was dealt with in [5]. We have proposed the use of semantic networks to describe 3-d structure in addition to representing function in the form of inference rules.

We have discussed only the representation of CNS structure. The structure of PNS is different in that it primarily consists of connective relationships of peripheral nerves; a method of representation is given in [5]. A semantic network representation of PNS structure is also currently under development [3].

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