

Causal Understanding of Patient Illness in Medical Diagnosis

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Abstract

First generation *AI in Medicine* programs have clearly demonstrated the usefulness of AI techniques. However, it has also been recognized that the use of notions such as causal relationships, temporal patterns, and aggregate disease categories in these programs has been too weak. From our study of clinician's behavior we realized that a diagnostic or therapeutic program must consider a case at various levels of detail to integrate overall understanding with detailed knowledge. To explore these issues, we have undertaken a study of the problem of providing expert consultation for electrolyte and acid-base disturbances. We have partly completed an implementation of ABEL, the diagnostic component of the overall effort. In this paper we concentrate on ABEL's mechanism for describing a patient. Called the *patient-specific model*, this description includes data about the patient as well as the program's hypothetical interpretations of these data in a multilevel causal network. The lowest level of this description consists of pathophysiological knowledge about the patient, which is successively aggregated into higher level concepts and relations, gradually shifting the content from pathophysiological to syndromic knowledge. The aggregate level of this description summarizes the patient data providing a global perspective for efficient exploration of the diagnostic possibilities. The pathophysiological level description provides the ability to handle complex clinical situations arising in illnesses with multiple etiologies, to evaluate the physiological validity of diagnostic possibilities being explored, and to organize large amounts of seemingly unrelated facts into coherent causal descriptions.

1. Introduction

We have studied difficulties arising in the operations of the "first generation" of AI programs in medicine and have undertaken the development of knowledge representation structures to support needed improvements. The description of a patient in existing programs such as INTERNIST-I [4], PIP [3], and MYCIN [6] starts from a single list of findings about the patient. Using a database of associations between diseases and findings (or rules establishing those connections), these programs form an interpretation of the patient's condition which is essentially a list of possible diseases, ranked by a calculated estimate of likelihood or degree of belief in each.

Researchers have recognized the need [2,5,7] to use notions such as causal relationships, temporal patterns, and aggregate disease categories in the description of a program's diagnostic understanding, but the mechanisms provided to do this have been too weak. For example, although causality appears as a term in descriptions in PIP and INTERNIST 1, in both cases its use is limited to guiding the propagation of likelihood measures. These programs fail to capture the human notion that explanation should rest on a chain of cause-effect deduction. Although, the CASNET/Glaucoma [10] program uses a network of causally-related states and defines diseases as paths in this network, its primary reasoning mechanism is nevertheless the local propagation of probability weights.

Similarly, it has been realized that a diagnostic or therapeutic program must consider a case at various levels of detail in order to integrate its overall understanding with its detailed knowledge. This insight also has not prevailed in the actual mechanisms provided in existing programs.

To explore the issues outlined here, we have undertaken a study of the medical problem of providing expert consultation in cases of electrolyte and acid-base disturbances. We have partly completed implementation of a program, ABIT., which is the diagnostic component of our overall effort. In

this paper we concentrate on ABEL's mechanism for describing a patient. Called the patient-specific model (PSM) [7], this description includes data about the patient as well as the program's hypothetical interpretations of these data in causal hierarchical networks. We describe the representations of medical knowledge and the processing strategies needed to enable ABEL to construct a PSM from the initial data presented to the program about a patient. The same representations and procedures will also be useful to revise the PSM during the process of diagnosis, but we will concentrate here on the logically prior operation of building the PSM.

Our understanding of medical expert reasoning suggests that an expert physician may have an understanding of a difficult case in terms of several levels of detail. At the shallowest that understanding may be in terms of commonly occurring associations of syndromes and diseases, whereas at the deepest it may include a biochemical and pathophysiological interpretation of abnormal findings. For our program to reason at a sophisticated level of competence, it will need to share such a range of representations. The PSM is, therefore, a multi-level causal model, each level of which attempts to give a coherent account of the patient's case. This model also serves as the basis for an English generation facility that provides explanations of the program's understanding.

The PSM is created by instantiating portions of ABEL's general medical knowledge and filling in its details from the specific case being considered. The instantiation of the PSM is very strongly guided by initially given data, because the PSM includes only those disorders and connections that are needed to explain the current case. Instantiation is accomplished by five major operators. *Aggregation* and *elaboration* make connections across the levels of detail in the PSM by filling in the structure above and below a selected part of the network, respectively. In a domain such as ABEL's, multiple disorders in a single patient and the presence of homeostatic mechanisms requires the program to reason about the joint effects of several mechanisms which collectively influence a single quantity or state. *Component decomposition* and *summation* relate disorders at the same level of detail by mutually constraining a total phenomenon and its components; the net change in any quantity must be consistent with the sum of individual changes in its parts. The final operator, *projection*, forges the causal links within a single level of detail in the search for etiologic explanations. The operators all interact because the complete PSM must be self-consistent both within each level and across all its levels. Therefore, each operation typically requires the invocation of others to complete or verify the creation of related parts of the PSM.

2. Hierarchical Representation of Medical Knowledge

Based on our observation that a physician's knowledge is expressed at various levels of detail, we have developed a hierarchical multi-level representation scheme to describe medical knowledge and procedures to instantiate this knowledge to describe a particular patient's illness. The lowest level of description consists of pathophysiological knowledge about diseases, which is successively aggregated into higher level concepts and relations, gradually shifting the content of the description from physiological to syndromic knowledge. The aggregate syndromic knowledge provides us with a concise global perspective and helps in the efficient exploration of diagnostic possibilities, the physiological knowledge provides us the capability of handling complex clinical situations arising in patients with multiple disturbances, evaluating the physiological validity of the diagnostic possibilities being explored, organizing large number of seemingly unrelated facts and

formulating therapy recommendations and prognosis. Finally, as the causal-physiological reasoning tends to be categorical and syndromic reasoning probabilistic, the hierarchical description allows us to blend together the use of categorical and probabilistic reasoning.(8)

2.1 Multi-Level Description of States

Medical knowledge about different diseases and their pathophysiology is understood to varying degrees of detail. While it may be easier for a program to reason succinctly with medical knowledge artificially represented-at a uniform level of detail, we must be able to reason with medical knowledge at different levels of detail to exploit all the medical information available. Although this does not pose any difficulty in medical domains where the pathophysiology of diseases is not well developed, in a domain such as electrolyte and acid-base disturbances where, on the one hand, the pathophysiology of the disturbances is well developed, and on the other, the pathophysiology of many of the diseases leading to these disturbances is relatively poorly understood, we are constantly faced with this problem.

Secondly, the information about a patient parallels the physician's medical knowledge about diseases and therefore also comes at different levels of detail. For example, "serum creatinine concentration of 1.5" is at a distinctly different level than "high serum creatinine",¹ and "lower gastrointestinal loss" than "diarrhea". We need some mechanism by which we can interrelate these concepts. Finally, in order to be effective in diagnostic problem solving and communicating with clinicians we ought to have the ability to portray the diagnostic problem in a small and compact space. Yet to be efficacious, we must maintain the ability to take every possible detail into consideration. We have solved this problem by representing the medical knowledge in five distinct levels of detail from a deep pathophysiological level to a more aggregate level of clinical knowledge about disease associations.

Each level of the description can be viewed as a semantic net describing a network of relations between diseases and findings. Each node represents a normal or abnormal physiological state and each link represents some relation (causal, associational, etc.) between different states. A state (interchangeably used with node) in the system such as "diarrhea" is represented as a node in the causal network. Each node is associated with a set of attributes describing its temporal characteristics, severity or value, and other relevant attributes. A state is called a *primitive-node* if it does not contain internal structure and is called a *composite-node* if it can be defined in terms of a causal network of states at the next more detailed level of description. One of the nodes in this causal network is designated as the *focus node* and the causal network is called the *elaboration structure* of the composite node. The focus node identifies the essential part of the causal structure of the node above it. Indeed, the collection of focal nodes acts to align the causal networks represented by different levels of the PSM. We note that very often a composite node and its focal description at the next level share the same name; this is typical in English, where the level of detail of place names, for example, is often obtained from context and not encoded in the name used. Nodes that do not play a role as the focal definition of any node at a higher level are called *non-aggregable nodes*. They represent a detailed aspect of the causal model which is subsumed under other nodes with different foci at less detailed levels of description.

	Lower-GI-fluid	Plasma-fluid
Na	100 - 110	138 - 145
K	30 - 40	4 - 5
Cl	80 - 90	100 - 110
HCO ₃	30 - 60	24 - 28

Fig. 1.

To illustrate the description of a state at various levels of aggregation, let us consider the electrolyte and acid-base disturbances that occur with diarrhea, which is the excessive loss of lower gastrointestinal fluid (lower GI loss). The composition of the lower gastrointestinal fluid and plasma fluid are as follows. In comparison with plasma fluid, the lower GI fluid is rich in bicarbonate (HCO₃) and potassium (K) and is deficient in sodium (Na) and chloride (Cl).

1. For a muscular patient whose previously known value of creatinine is 1.3 we can assume this to be normal, but for a patient with a previously known value of 1.0 this is definitely high and could imply a loss of about 1/3 of the kidney function.

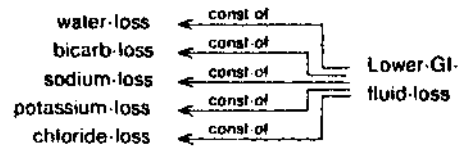


Fig. 2.

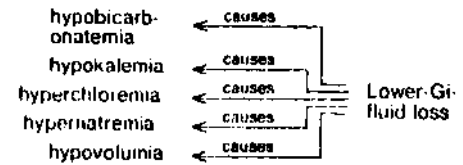


Fig. 3.

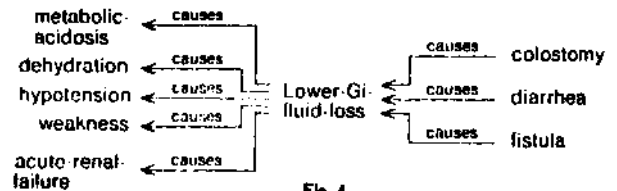


Fig. 4.

This information is represented in the knowledge base by decomposing lower GI loss into its constituents (and associating appropriate quantitative information with the decomposition). The loss of lower GI fluid would result in the loss of corresponding quantities of its constituents (in proportion to the total quantity of fluid loss) as shown in fig 2. Therefore, an excessive loss of lower GI fluid without proper replacement of fluid and electrolytes would result in a net reduction in the total quantity of fluid in extracellular compartment (hypovolemia). Because the concentration of K and HCO₃ in lower GI fluid is greater than in plasma fluid, there is a corresponding reduction in the concentration of K (hypokalemia) and HCO₃ (hypobicarbonatemia) in the extracellular fluid. Finally, as the concentration of O and Na in the lower GI fluid is lower than that in plasma fluid, there is an increase in the concentration of Cl (hyperchloremia) and Na (hypernatremia) in the extracellular fluid. This is represented at the next level of description as shown in fig 3. Fig. 4 shows the aggregation of this information along with some additional causes and consequences of lower GI loss at the next more aggregate level of detail. The lower GI loss at this level is a non-aggregable state and therefore does not have an aggregation at the next level above. Fig. 5 shows the description of the aggregate effects of diarrhea (one of the causes of lower GI loss). The summarization of the description of lower GI loss and diarrhea shown in fig. 5 is achieved through the use of link aggregation and elaboration, described in the next subsection.

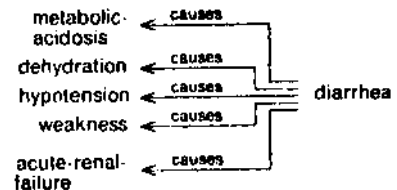


Fig. 5.

2.2 Multi-Level Description of Causal Links

A causal link specifies the cause-effect relation between the cause (the antecedent) and the effect (the consequent) states. In past programs (e.g., PIP, INTERNIST), causal links were described by specifying the type of causality (may-be-caused-by, complication-of, etc.), and a number or a set of numbers representing in some form the likelihood (conditional probability), importance, etc., of observing the effect given the cause or vice versa. We now believe that this simple representation of the relation between states is inadequate. The form of presentation of an effect and the conditional probability of observing it depends upon various aspects of the cause such as severity, duration, etc., as

well as other factors in the context in which the link is invoked^{2a} (such as the patient's age, sex and weight, and the current hypothesis about the patient). Therefore a causal link in the system (an object denoting the causal relation between a cause-effect pair) specifies a multivariate relation between various aspects of the cause and effect, and also specifies the context and assumptions which constrain the causal relation, as shown in fig. 6.

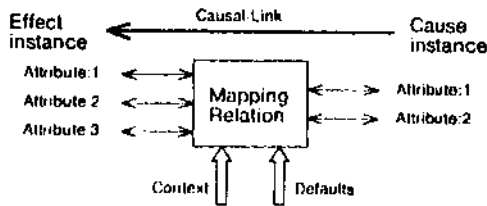


Fig. 6.

One important function of diagnostic reasoning is to relate causally the diseases and symptoms observed in a patient. These causal relations play a central role in identifying clusters that can be meaningfully aggregated in developing coherent diagnoses. The presence or absence of a causal relation between a pair of suites can change their diagnostic and prognostic interpretations. Therefore, the system should and does have the capability of hypothesizing the presence or absence of a causal link. It is the reason why links are objects in their own right rather than simple pointers between nodes.

To reason with a causal network representation effectively, a program must make conclusions about a node or link depending only on information that is locally available from the neighborhood of the mechanism in question. If non-local effects are to be invoked in causal explanations, they must be explicitly identified (e.g., as part of the context of the causal link) or else they corrupt our ability to reason with any portion of the network. If at some level of detail two distant phenomena interact, we must aggregate the description of the causal network to a level where the two phenomena are adjacent to one another. Further, because the causal relations specified by links are not guaranteed to be true under all circumstances (they represent strong associations, not logical truth), the validity of deductions degrades with every additional intermediate link. That is, a causal pathway containing a large number of links is less likely to be valid than one using only a few links. Therefore, in order to explore a large diagnostic space, we must aggregate the diagnostic space to a level where each link represents an aggregate causal phenomenon covering larger distances and thus minimizing the possibility of error in the deduction. This ability to move from one level of description to another is provided by the multi-level description proposed here.

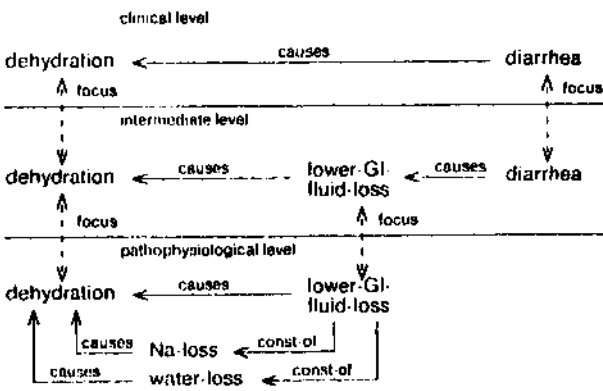


Fig. 7.

Links can be categorized, as nodes are, into two types: the *primitive links* and the *composite links*. To illustrate the concept of elaborating causal links to form a causal pathway, let us consider the causal relation between diarrhea and dehydration shown in fig. 7. The causal mechanism of diarrheal-dehydration

² For example, a severe diarrhea causes severe hypokalemia, and a mild diarrhea causes mild hypokalemia.

can be elaborated as follows: diarrhea causes lower GI loss, which causes dehydration. Expressed at the next level of detail, the lower GI fluid loss can be described as consisting of the loss of water and sodium along with other electrolytes. The water loss in the presence of the reduced total quantity of extracellular sodium results in lower extracellular volume, which at the higher level of description is described as dehydration.

3. Reasoning About Components

One of the important areas of medical diagnosis not adequately addressed by the first generation of AIM programs is the evaluation of the effect of more than one disease present in the patient simultaneously, especially when one of the diseases alters the presentation of the others. This problem does not place serious limitations on programs dealing with single problems such as the therapy of glaucoma or the diagnosis of bacteremia. But, in the case of electrolyte and acid-base disturbances where a large fraction of cases involve multiple diagnoses, the ability to evaluate the joint influence of multiple disease and the ability to decompose their influences on observable findings is particularly important.

For example, let us consider a patient with diarrhea and vomiting leading to severe hypokalemia. Let us also suppose that we know about the diarrhea, but we are not aware of the vomiting. The observed hypokalemia is too severe to be properly accounted for by the diarrhea alone. Without the ability to decompose the hypokalemia, we would have to attribute it completely to the diarrhea or completely to something else. In either case³ we fail because the total state of hypokalemia is inconsistent with any of its possible single causes. Thus, any single cause hypothesized by the program (e.g., vomiting) will not be severe enough to account for the observed hypokalemia by itself. As argued above, we need the ability to hypothesize that only a part of the hypokalemia is accounted for by diarrhea. We introduce the notion that any primitive node in the causal hierarchy⁴ may have *components*, which are other primitive nodes which together make up the given node.

In our system this is achieved by a pair of operators: *component summation* and its dual *component decomposition*. Using our example, these operators allow us to attribute only a part of hypokalemia to the diarrhea and to compute that part of hypokalemia that is not caused by diarrhea (called the *unaccounted component* of the hypokalemia). These operations deal not only with the magnitude of some disorder but also with other attributes such as duration. They are implemented by associating with each primitive node a multivariate relation that constrains attributes of the node and its constituents. Component summation combines attributes of the components to generate the attributes of the joint node; component decomposition identifies unaccounted components by noting differences between the joint node and its existing components. These operations enrich the PSM by instantiating and unifying together component nodes when the case demands them. This occurs whenever multiple causes contribute jointly to a single effect. An important case of this arises whenever feedback is modeled, because in any feedback loop there is at least one node acted on by an outside factor and by the feedback loop itself.

As the PSM is built, component summation and decomposition operations can cause a node in the program's general knowledge to be instantiated as a node and its several components. If a node is primitive and there are multiple causes, the contribution of each cause is instantiated separately. Then the profile of the combination is computed using component summation. The combined effect is then instantiated and connected to its constituents by constituent links.

Because components are defined only for primitive nodes, the instantiation of composite nodes which involve component summation must be in terms of the summation of components in the nodes' elaboration structure. If the node is composite then we elaborate the constituent nodes around their focal nodes until we reach the primitive nodes associated with them at a level of greater detail. Then we combine these primitive nodes and aggregate their effects

³ All the previous programs would allow the entire hypokalemia to be accounted for by diarrhea. In particular, PIP after allowing the hypokalemia to be accounted for by diarrhea will not allow hypokalemia to lend any support to the hypothesis of vomiting. INTRINSIC, on the other hand, will allow the entire hypokalemia to lend support to the hypothesis of vomiting as well as allowing it to be explained by diarrhea.

⁴ Recall that primitive means that it is not the aggregation of a further-defined causal structure.

back. For example, if we know that a patient has two disturbances, diarrhea and shock, causing metabolic-acidosis (Fig. 8), then we evaluate their contribution to metabolic-acidosis and then focally elaborate the two constituents until the metabolic-acidosis is described in terms of the quantity of serum bicarbonate lost.⁵ We then aggregate the joint effects to derive the actual severity of metabolic-acidosis.

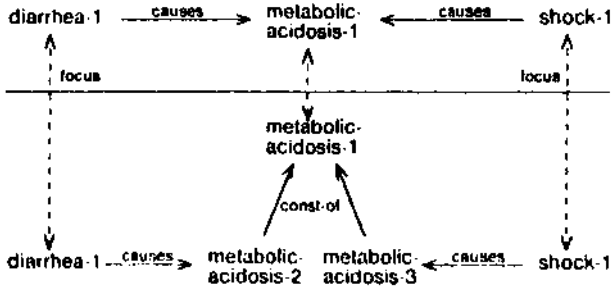


Fig. 8.

As mentioned above, the mechanism of component summation allows us to represent feedback explicitly by representing the primary component of the change (the forward path) and the secondary feedback component (the response of the homeostatic mechanism in defense of the parameter being changed) as components to be summed to yield the whole. Fig. 9⁶ shows the primary change in serum pH caused by low serum bicarbonate and the response of the respiratory system in defense against the change in serum pH. Read the example as follows: the lowering of the concentration of serum bicarbonate causes a reduction in serum pH, which causes hyperventilation and thus reduces the pCO₂, which in turn causes an increase in the serum-pH (negative feedback). This increase is less than the initial reduction, causing a net reduction in serum pH. The decomposition of an effect with multiple causes into its causal components also provides us with valuable information in evaluating prognosis and in formulating therapeutic interventions.

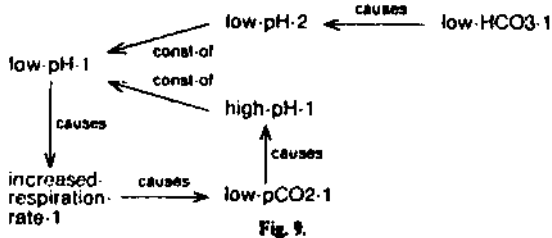


Fig. 9.

4. The Patient Specific Model

Diagnosis is the process of actively seeking information and identifying the disease processes causing the patient's illness. In other words, diagnosis involves ascertaining the facts and their implications. The effectiveness of the information gathering process depends on the analysis of the available facts. From our experience with the existing diagnostic systems [3,4], we are convinced that a relatively simple representation of physician's analysis of patient's illness (i.e., a list of disease hypotheses) is incapable of providing the desired level of expertise. The patient description must unify all the known facts about the patient, their interpretations, their suspected interrelationships and disease hypotheses in order to explain these findings. Finally, we observe that at any point in diagnostic reasoning practiced by human experts, there are only a few significantly different explanations for the patient's illness under consideration.

In the program, each such explanation is represented by a patient specific model (PSM). Note that within each PSM all the diseases, findings, etc., are mutually complementary, while the alternate PSM's are mutually exclusive and competing. In this section we describe procedures for building and extending a patient specific model based on the known findings and the program's medical knowledge. These operations are *initial formulation* to create an initial patient description from the presenting complaints and laboratory results, *aggregation* to summarize the description at a given level of detail to the next more aggregate level, *elaboration* to elaborate the description at a given level of

aggregation to the next more detailed level and *projection* to hypothesize associated findings and diseases suggested by states in the PSM.

4.1 Initial Formulation

From observing the clinical behavior of physicians, we have noticed that when presented with the chief complaints and other voluntarily provided information in a case, the physicians set up a tentative diagnosis. This diagnosis serves as a specific framework which can be used in soliciting information and for organizing the incoming information. Similarly the program when provided with the initial findings and a set of serum electrolyte values constructs a small set of PSM's as its initial possible diagnoses, using the following steps. First it analyses the electrolytes and formulates all possible single or multiple acid-base disturbances that are consistent with the electrolyte values provided and selects from them a small set which is consistent with the initial findings. Next, it generates a pathophysiological explanation of the electrolytes based on each of the proposed acid-base disturbance. This is performed by elaborating all known clinical information to the pathophysiological level, where its relationships to the laboratory data are determined by projecting the unique causes and definite consequences of every node. Then the program summarizes these pathophysiological descriptions to the clinical level by repeated application of aggregation operations. This process results in the initial description of the patient at every level of detail. It is this description which is later modified by the diagnostic process as new information becomes available. Note that each of the mechanisms, aggregation, elaboration and projection are used in the initial formulation of the PSM.

4.2 Aggregation

The aggregation process allows us to summarize the description of the patient's illness at any given level to the next more aggregate level. The summarization of a causal network can be achieved by recognizing that a central node and its surrounding causal relationships may be expressed at a more aggregate level by a single node (called *focal aggregation*), and by summarizing a chain of relations between nodes by a single causal relation between the initial cause and the final effect nodes (called *causal aggregation*).

4.2.1 Focal Aggregation

In aggregating a causal network we must first identify the nodes in the network that form anchor point (i.e., landmarks; points of special significance) around which the causal phenomenon can be summarized. Consider a partially-completed PSM in which some nodes at a detailed level of aggregation have been instantiated. Any of these nodes is an anchor point if: (1) in the medical knowledge base such a node is the focus of some node at the next more aggregate level in the network, and (2) at least one such higher level node already exists or can be instantiated within the PSM. If it exists and the constraints on the focal link are satisfied, then the focal link connecting the two is insinuated. If it does not exist, then both it and the focal link are insinuated. Finally, if more than one possible description of the node is consistent with the causal structure above, we defer the aggregation process until we can obtain some additional information to resolve this ambiguity.

4.2.2 Causal Aggregation

Once we have determined the focal aggregations for nodes at a given level of aggregation we need to describe the causal relations among these aggregate nodes. The process of causal aggregation takes a node and its causes and aggregates the relation between them according to one of three rules. First, if the node has no causal predecessors or if none of the causal paths leading into the node (called *predecessor paths*) have a node with a focal aggregation then the focal aggregation of the node either is an ultimate etiology or is totally unaccounted for and does not need to be causally aggregated. Second, if every predecessor path has a node with a focal aggregation then the focal aggregation of the node is fully accounted for. The causal aggregation is achieved by instantiating a causal link between the focal aggregation of the node and the first focal aggregation in each path. Finally, if only some of the predecessor paths have nodes with focal aggregations then the focal aggregation of this node is partially accounted for. The causal aggregation is achieved by decomposing the node into two components: 1) due to paths which have focal aggregation (called *accounted component*); and 2) due to paths that do not (called *unaccounted component*). Then, the focal aggregation of the node is decomposed based on the decomposition at the present level and the two cases are treated as described above.

4.3 Elaboration

Elaboration is the dual of the aggregation operation described above and is used to elaborate the description of a causal network at a given level of

aggregation to the next more detailed level. This is achieved by elaborating each link in the causal network by first describing the cause and effect of the link at the next more detailed level (called *focal elaboration*) and then instantiating the causal pathway between these detailed nodes (called *causal elaboration*). If the causal pathway being instantiated interacts with other causal paths in the PSM the combined effects of the multiple causality are computed using component summation. The combined effects of this summation can then be aggregated to reflect the better understanding of the causal phenomenon at higher levels of aggregation.

4.5.1 Focal Elaboration

Focal elaboration is the inverse of focal aggregation. To focally elaborate a composite node the program computes the possible profile of the focal concept associated with the given node. If a node at the next lower level of aggregation matches this profile and is consistent with the node above, it instantiates the focal link connecting the two. If not, it instantiates the focal node and the focal link connecting the two.

4.3.2 Causal Elaboration

Causal elaboration is the dual of causal aggregation. A composite causal link can be elaborated if the cause and the effect nodes of the link have focal elaborations. To elaborate a composite link the program matches the causal path associated with the link starting at the focal nodes of the cause and the effect of the link with existing paths in the PSM. If some part of this pathway is not present in the PSM, the program recursively calls itself on each link in the pathway (starting from the focus node of the source) that is absent in the PSM. If the link being recursively elaborated is a primitive link and if its effect node is not present in the PSM, the effect node and the link are instantiated. Otherwise, if the effect node is present, it matches the attributes of the cause and the effect nodes. If they are compatible, it instantiates the link. Otherwise, if the effect node is an observed node, the program decomposes the effect node and instantiates the link connecting the cause and the component of the effect node contributed by it. Otherwise, if the effect node is accounted for by some other cause, it instantiates the combined effect by summing the components of the two causes. Finally, it aggregates the effect node to revise the description at the next more aggregate level.

4.4 Projection

The Projection operation is used to hypothesize and explain the associated findings and diseases suggested by the states in the PSM. The projection operation is very similar to elaboration. It differs from elaboration in that the causal relation being projected is hypothetical and therefore is not present in the PSM. Furthermore, the projection operation fails if the causal description of the hypothesized link is inconsistent with the description in the PSM at any level of aggregation. As a result, the application of the projection operation cannot result in the decomposition of a fully accounted node, creating an additional unaccounted component and therefore degrading the quality of explanation.

We envision using the projection operation in the diagnostic problem solver for exploring diagnostic possibilities, evaluating their physiological validity and in generating expectations about the consequences of hypothesized diagnoses.

5. An Example

Let us consider a 40 year old 70 Kg patient who has been suffering from moderately severe diarrhea for the last two days and, as a result, has developed moderately severe metabolic acidosis and hypokalemia. The laboratory analysis of the patient's blood sample (serum analysis) is; Na: 140, K: 3.0, Cl: 115, HCO_3^- : 15, pCO_2 : 30, and pH: 7.32.

5.1 Initial Formulation

To exercise the program, let us provide it initially with only the laboratory data. Based on these data, the program generates all possible acid-base disturbances that can account for the laboratory data. They are:

1. metabolic-acidosis
2. chronic-respiratory-alkalosis + acute-respiratory-acidosis
3. metabolic-acidosis -f chronic-respiratory-alkalosis
+ acute-respiratory-acidosis
4. metabolic-alkalosis + chronic-respiratory-alkalosis
+ acute-respiratory-acidosis.

Based on the complexity,⁸ likelihood and severity of each component, the list of possible disturbances is pruned and rank-ordered. The rank-ordered list of likely disturbances is

1. metabolic-acidosis (severity: 0.4)
2. chronic-respiratory-alkalosis (severity: 0.68)
+ acute-respiratory-acidosis (severity: 0.32).

The program now creates a PSM¹⁰ for each possible acid-base disturbance and assembles instantiations of the laboratory data (at the pathophysiological level) and the appropriate acid-base disturbances (at the clinical level). In the rest of the example we will focus on the first acid-base disturbance, namely metabolic acidosis. The program focally elaborates the metabolic acidosis through the intermediate levels until it reaches the pathophysiological level and thus identifies the amount of HCO_3^- loss corresponding to the severity of the metabolic-acidosis. Based on this information and the laboratory data, it instantiates the feedback loop corresponding to the acid-base homeostatic mechanism. Next, it projects back each node whose cause can be uniquely determined and projects forward the definite consequences of each node in the PSM. We now have the pathophysiological level explanation of the electrolytes consistent with the diagnosis of metabolic-acidosis as shown in fig. 10.

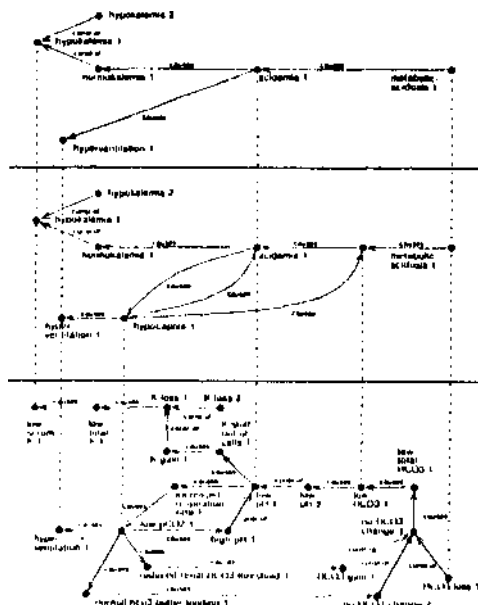


Fig. 10. Initially formulated PSM

5.2 Aggregation

After the pathophysiological description is completed, this description is aggregated through the intermediate levels to the clinical level of detail. To illustrate this operation let us consider the low-serum-K-I node at the pathophysiological level. Focally aggregating this node, we instantiate hypokalemia-1 as shown in fig. 10. To determine the causal aggregation of this node at the next level of detail we must focally aggregate the first aggregable node in each path leading back; in this case low-pH-1. Focally aggregating low-pH-1 we instantiate acidemia-1. Next, we compute the component of low-serum-K that can be accounted for by low-pH-1 and the component that remains to be accounted for because of the unaccounted K-loss-2. Then we compute the mapping of these components at the next level of aggregation and instantiate normokalemia-1 (the component accounted for by low-pH-1) and hypo-

7 or if the effect node is a causal predecessor of some observed node that completely accounts for it

8 triple disturbances are quite rare and are generally not considered during initial formulation unless there is compelling evidence for their presence.

9 The rank ordering of the diseases is based on Occam's Razor — simpler hypotheses are preferred

10 For ease of explanation, the example described here uses a three level PSM instead of the five level PSM used in the program

11 Note here that as we are at pathophysiological level, each link being projected is primitive. Thus, projecting back at this level can be restated as instantiating the cause and the link connecting the cause and the effect node

kalemia-2 (due to unaccounted K-loss-2). We then connect the normokalemia-1 to acidemia-1 and mark the hypokalemia-2 as unaccounted (indicated in the figure by an asterisk). Next, in order to causally aggregate low-pH-1 we focally aggregate low-pCC⁻¹ and 10W-HCO₃-1 into hypocapnia-1 and hypobicarbonatemia-1 respectively. As each path leading back from low-pH-1 terminates in a node with focal aggregation, the focal aggregation of low-pH-1 (acidemia-1) is fully accounted node. Therefore, we connect acidemia-1 to hypocapnia-1 and hypobicarbonatemia-1. This process is repeated for each aggregable node at the current level and then the whole process is repeated at the next level until we reach the clinical level of aggregation

5.3 Projection

To illustrate the projection operator, let us assume that the diagnostic component has hypothesized that the unaccounted component of hypokalemia at the clinical level (hypokalemia-2) is caused by diarrhea and wishes to determine if this is so and how this assumption fits with the current PSM. The result of this operation is shown in fig. 11.

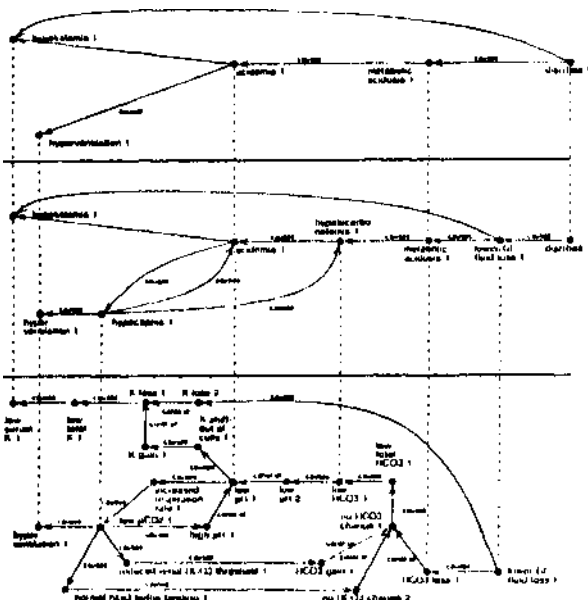


Fig. 11. PSM extended to include Diarrhea

To project the link between hypokalemia and diarrhea the program evaluates the link to determine the attribute profile of the diarrhea consistent with hypokalemia-2 from which it determines the profile of diarrhea at the next more detailed level, it then attempts to match the causal path associated with the link (hypokalemia <- lower-GHoss <- diarrhea) at the next level. As none of the links in this pathway are present and as this causal pathway is consistent with the description at the next level, the program recursively calls itself on each link in the path. Considering the first link (that is hypokalemia <- lower-GHoss), it finds the causal path associated with this link at the next level of detail (low-serum-K <- low-total-K <- K-loss <- lower-GHoss). Matching this path with the description in the PSM, it finds that all but one link (K-loss <- lower-GHoss) is already present. Since this link is primitive, the program evaluates the profile of the lower-GHoss consistent with the unaccounted component of K-loss and instantiates it and the causal link connecting lower-GHoss-1 to K-loss-2. To reflect this addition at the higher levels of detail, the program aggregates the low-serum-K-1 (the effect node in the path). As the low-serum-K-1 is now a fully accounted node, the component structure associated with its focal aggregation (hypokalemia-1) is deleted and the causal links associated with the accounted component of hypokalemia-1 and an additional link from lower-GHoss-1 are connected to it. This process is repeated until we establish the relation between the diarrhea and hypokalemia at the clinical level.

5.4 Elaboration

The process of elaboration is similar to that of projection described above and differs from it in two major ways. 1) the causal link and the associated nodes already exist in the PSM at the higher level of aggregation and 2) we have already determined that the causal link being elaborated is valid. Therefore if a causal pathway associated with the link at some level of detail is not consistent with the description in the PSM, the program modifies the PSM appropriately to accommodate the pathway. In the example being described the second (and more interesting) case does not arise, to demonstrate the elaboration process let us establish the relation between diarrheal and metabolic-acidosis-1 at the clinical level. The result of elaborating this link is shown in fig. 11.

6. English Explanation

To illustrate the program's understanding of the patient's illness at various levels of detail, an English generator was implemented to translate the PSM at any given level into *us English* description'. The descriptions are given at three levels of detail in fig. 12.

Clinical Level

This is a 40 year old 70.0 kg male patient with moderate diarrhea. His electrolytes are:

Na: 140.0 HCO₃: 15.0 Agap: 13.0
 K: 3.0 pCO₂: 30.0
 C1:115.0 pH:7.32

The diarrhea causes moderate metabolic acidosis, which causes mild acidemia. The acidemia and diarrhea cause mild hypokalemia and acidemia causes hyperventilation. All findings have been accounted for.

Intermediate Level

This is a 40 year old 70.0 kg male patient with moderate diarrhea. His electrolytes are:....

The diarrhea causes moderate lower GI loss, which causes moderate metabolic acidosis. The metabolic acidosis along with moderate hypocapnia causes moderate hypobicarbonatemia. The hypobicarbonatemia along with hypocapnia causes mild acidemia. The acidemia and lower GI loss cause mild hypokalemia and acidemia causes hypocapnia. The acidemia also causes hyperventilation. All findings have been accounted for.

Pathophysiological Level

This is a 40 year old 70.0 kg male patient with moderate lower GI loss. His electrolytes are:....

Moderate lower GI loss, reduced renal HCO₃ threshold and normal HCO₃ buffer binding jointly cause no HCO₃ change and no HCO₃ change causes low ccf HCO₃, which causes low serum HCO₃. The low serum HCO₃ and low serum pCC^{>2} jointly cause low serum pH. The low serum pH causes K shift out of cells and causes increased respiration rate. The increased respiration rate causes low serum pCO₂, which causes no HCO₃ buffer binding. The low serum pCO₂ also causes reduced renal HCO₃ and increased respiration rate causes increased ventilation. The lower GI loss and K shift out of cells jointly cause K loss. The K loss causes low ccf K, which causes low serum K. All findings have been accounted for.

Fig. 12. English explanation at different levels of detail

7. Conclusion

We have begun a complex and challenging task: to reason about difficult medical problems with a representation that is capable of capturing the subtlety and richness of knowledge and hypotheses used by expert physicians. We have thus far succeeded in creating a representation and a set of structure building operators which are able to create a patient description based on causal models, multiple levels of detail in description, and the explicit use of components of quantities and states. The various viewpoints on the patient represented by 'different cuts through this complex description' are kept consistent by the

12 The generator makes use of the methodology and some of the code of a generator built by William Swartoui as part of an interactive system which explains and justifies portions of expert programs [9]

operators. We believe that this approach displays a level of understanding not achieved before in medical reasoning programs or others which need to describe an organization of hypotheses or mechanisms at different levels of detail.

In continuing to develop our diagnostic and therapeutic programs, we believe that the organizational framework provided by the PSM and its associated operators gives us a suitable machinery for exploring the choice of reasoning strategies and recording our programs' changing conceptions of a case. The rich network of interconnections in the PSM constrains a diagnostic reasoner to generate only a relatively small number of coherent explanations, thereby reducing the space of possibilities to be investigated in seeking a diagnosis. In particular, enforcing the requirements of causal consistency (at each appropriate level of detail) on any tenable explanation provides a means of pruning the diagnostic space and permits us to try a "hypothesize and debug" reasoning strategy. The multiple level interconnections of the PSM also help us merge decisions and considerations we have described as categorical and probabilistic. Although much work clearly remains before developments such as those described here form the fabric of truly successful medical consulting systems, we have proposed here a useful new representational basis for such work.

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