Clinical Reasoning System Based on Clinicians’ Diagnostic Process

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Abstract—The paper first describes a model of clinicians’ diagnostic process and discusses how the clinicians diagnose their patients. It is important to detect possible critical diseases at early stage of medical diagnosis regardless of their frequency or probability. Therefore, we propose a system that applies inverse causal reasoning to diagnose possible diseases from observed clinical information, which is based on possibilistic causal relations between diseases and clinical information. Most of clinical diagnosis systems proposed so far adopt single disease assumption. However, multiple diseases often occur simultaneously in clinical reasoning. The paper also discusses the assumption of multiple-diseases to support the clinical reasoning. 

Keywords: Clinical Reasoning, Inverse causal reasoning, Possibility Theory, Medical support diagnostic system.

I. INTRODUCTION

Use of IT applications in the health care field is rapidly evolving beyond the frame of so-called Clinical Information System. Clinical information system is a comprehensive and integrated information system designed to manage the administrative, financial and clinical aspects of a hospital. However, most of existing clinical information systems mainly focuses on improving efficiency of medical operation and reducing the total medical cost. With growing scope and complexity of medical information, clinicians are finding it difficult to stay abreast of the most up-to-date medical knowledge. The rapidly increasing availability of information has coincided with fundamental change in the structure and delivery of medical care. In those difficult environments for clinicians, the need of a system that supports clinicians’ clinical reasoning is increasing.

The system image needed is a system that has a strong capability of reasoning according to the clinicians’ diagnosis process. The clinicians narrow the list of diseases with high possibility from the sequentially given clinical information (hereafter may be called symptoms) based on the exclusive knowledge and experience. The diagnostic process that narrows down the diseases from the symptoms can be considered as an inverse problem of typical causal relation between diseases and symptoms [1].

There might be many conditions required for practical systems. In the paper, we assert that the following four conditions are very important to make a clinical reasoning system practical:

(1) Clinical reasoning that follows the clinicians’ problem solving and diagnostic process,

(2) Capability to detect low frequent but serious diseases,
(3) Capability to detect multiple diseases if they actually arise simultaneously.

(4) Simple representation and easy acquisition of knowledge.

To satisfy the condition (1), the paper develops a model of clinicians’ diagnostic process and discusses how to support the doctor’s reasoning in the process. Then, it clarifies the importance of sequential reasoning to narrow down the diagnostic hypothesis from sequentially given symptoms.

To satisfy the condition (4), we use causal relations between diseases and symptoms as knowledge, which could be represented by rules from diseases to symptoms (D-S rules). Most of rule-based medical expert systems [2], [3] employ the judgment rules with the opposite direction (S-D rules), because diseases can be derived from symptoms by deduction or simple pattern matching. However, it is well known that the S-D rules have serious problems in knowledge acquisition. The paper discusses that the problems can be solved by the usage of causal relations as knowledge.

In the causal knowledge used in diagnosis, uncertainty is usually included. That is, there are many cases where a cause may or may not cause an effect. An important problem of using probability as uncertainty in medical diagnosis is that a serious disease may be eliminated from the candidate list due to its very low occurrence, which is mentioned as the condition (2). The paper discusses the problem and points out that possibilistic causal model can relieve the problem.

Most of diagnostic systems proposed so far are based on single disease/fault assumption. However, multiple diseases often occur simultaneously in the case of clinical diagnosis, especially in the case of the elderly. Thus, the clinical reasoning system must be able to cope with the cases with multiple diseases as shown in condition (3).

The paper proposes a clinical reasoning system which satisfies all the above four conditions, which is a system with the function of sequential narrowing-down, using the possibilistic causal knowledge, and based on the multiple-disease assumption.

II. CLINICAL REASONING PROCESS

The process of diagnosis begins when the patient consults the doctor and presents a set of complaints (the symptoms). The doctor then obtains further information from the patient himself about the patient's symptoms, his previous state of health and living conditions.

Clinicians generate a list of possible causes to better understand a patient's symptoms. Rather than considering myriad diseases that could afflict the patient, the clinician narrows down the possibilities to the illnesses likely to account for the apparent symptoms, making a list of only those diseases that could account for what is wrong with the patient. These are generally ranked in the order of probability.

The clinician then conducts a physical examination of the patient, studies the patient's medical records, and asks further questions as he goes, in an effort to rule out as many of the potential diseases as possible. When the list is narrowed down to a single disease, this is called the differential diagnosis, and provides the basis for a hypothesis of what is ailing the patient [5].

Unless the clinician is certain of the disease present, further medical tests are performed (such as medical imaging), in part to confirm or disprove the diagnosis. If unexpected findings are made during this process, the initial hypothesis may be ruled out and the clinician must then consider other hypotheses.

Despite all of these complexities, most patient consultations are relatively brief, because many diseases are obvious, or the clinician's experience may enable him to recognize the condition quickly. Another factor is that the decision trees used for most diagnostic hypothesis testing are relatively short.

Once the clinician has completed the diagnosis, he proposes a treatment plan which includes therapy and follow-up, usually according to the guideline provided by the medical field on the treatment of the particular illness.

Treatment itself may indicate a need for review of the diagnosis if there is a failure to respond to treatments that
would normally work.

Some Internal Medicine researches show 56-83% of clinician hypotheses match the final diagnosis from patient consults, 70-90% matches the final diagnosis when simple physical findings is done [6].

III. REQUIREMENTS FOR CLINICAL REASONING

This section clarifies the needs for a clinical reasoning system according to the clinicians’ reasoning process. During the diagnostic process, Information about the symptoms is not obtained at a time collectively. It is obtained one by one asynchronously in each phase of the diagnosis. The order of information acquired changes dynamically depending on what information is acquired in the previous step.

For example, the clinical examination and the screening inspection are decided based on the hypotheses narrowed down from the symptoms obtained before. It is important to input the symptoms one by one to narrow the hypotheses in every phase of diagnosis. This paper defines it as sequential reasoning as the first requirement.

There are diseases that arise rarely but are serious. In the practical diagnosis, it is crucially important that possible serious diseases remain in the final hypotheses even if their occurrence probabilities are very low. However, when applying probabilistic models to these rare but serious diseases, they tend to be eliminated from the hypothesis list because the final probabilities become very low. This paper calls it rare serious disease problem, and defines the relief of the problem as the second requirement.

Most of typical diagnostic systems are based on the single disease/fault assumption. However, in the case of clinical diagnosis, it is not unusual that multiple diseases arise at the same time. The reason why the single disease assumption is so common is that handling of multiple diseases causes so-called the computational explosion. This paper defines the handling of multiple diseases assumption as the third requirement.

The fourth requirement is solution or relief of the knowledge acquisition problem. Any diagnostic system needs the knowledge base that plays a vital role to its capability. The difficulty of acquiring specialist’s empirical knowledge is widely known. The empirical knowledge for the medical diagnosis is usually expressed by the S-D rules (IF the symptoms are A1 and A2, then the disease is B). It is a very time-consuming task to draw out the clinician experience and intuition in the form of rules. In addition, symptoms of a disease are not always the same. Therefore the knowledge base should have many rules having different conditions in the IF part for a disease.

The real medicine knowledge of diseases is often described in the form of the cause and effect knowledge, i.e. the D-S rules (Disease B causes symptoms A1 and A2). If multiple symptoms can be described in the result part, and the uncertainty is introduced in the causal relation, the knowledge about a disease and its symptoms can be described by a rule. Therefore, knowledge representation by the causal relation could relieve the problem of knowledge acquisition.

IV. CLINICAL REASONING MODEL

This section describes an approach to realize the clinical reasoning that satisfies the four requirements mentioned in the previous section. The paper first introduces abductive reasoning [8] and possibilistic inverse causal reasoning [7], [9]. Then, it discusses that the four requirements are satisfied by combining the two reasoning.

A. Abductive Reasoning

Peng and Reggia [8] define a general diagnostic problem by a four-tuple \( < D, M, C, M^+ > \), where \( D \) is a set of possible diseases, \( M \) is a set of possible symptoms of diseases in \( D, C \subseteq D \times M \) gives causal relations among diseases and symptoms, and \( M^+ \subseteq M \) is a set of observed symptoms, where \( D \times M \) is Cartesian product of \( D \) and \( M \), and \( M^+ \subseteq M \) means that \( M^+ \) is a subset of \( M \).

Elements of \( C \) are represented by \( < d_i, m_j > \), \( d_i \in D \), \( m_j \in M \), i.e. \( d_i \) and \( m_j \) are elements of \( D \) and \( M \).
respectively. \( < d_i, m_j > \) means that disease \( d_i \) may cause symptom \( m_j \).

The abductive reasoning derives (a) subset(s) of \( D \) called explanation, which could cause all the observed symptoms in \( M^+ \) if all the diseases in an explanation arise. Explanations are subsets \( E_k \subseteq D \) \((k = 1,...,K)\) satisfying the following formula:

\[
\{M^+ \subseteq \text{effects}(E_k)\} \land \{S \subseteq E_k; M^+ \subseteq \text{effects}(S)\} \tag{1}
\]

where \( \land \) and \( \neg \) are logical conjunction and negation, respectively. \( S \subseteq E_k \) means that \( S \) is a proper subset of \( E_k \), and \( \text{effects}(E_k) \) is the set of symptoms possibly caused by the diseases in \( E_k \).

Since the explanation \( E_k \) is a subset of \( D \), the subsets that must be checked whether they are explanations or not amounts to \( 2^{|D|} - 1 \), where \( |D| \) is the cardinality of the set \( D \). Therefore, the combinational explosion would arise if all the explanations are searched directly.

Fortunately, however, a fast sequential algorithm to obtain all explanations has been proposed, which derives all explanations of \( M^+ \cup \{m_j\} \) quickly when all the explanations \( E = \{E_1,...,E_K\} \) of \( M^+ \) are given, where \( \cup \) is a union, and \( m_j \notin M^+ \). See [8] for the details.

**B. Causal reasoning with conditional causal possibilities**

Possibility theory [11] is an uncertainty theory to handle incomplete information similar to Probability theory. It differs from the latter by the use of a pair of dual set-functions (possibility and necessity measures) instead of only one. This feature makes it easier to capture partial ignorance.

Let \( \pi(x) \) be a possibility distribution on a discrete universal set \( X \), and \( \Pi(A), A \subseteq X \) be the possibility measure specified by \( \pi(x) \). Then, the following must be satisfied:

\[
\forall x \in X \pi(x) = 1, \tag{2}
\]

\[
\Pi(A) = \bigvee_{x \in A} \pi(x), \tag{3}
\]

where \( \bigvee \) denotes maximum when used for possibilities. See [11] for the details.

Probability theory is usually used to handle uncertain information. Probability is a ratio scale of uncertainty. It is well known that a small difference between the given and the real probabilities may produce wrong reasoning results for ordering uncertainty. Thus, probabilities should be given as accurately as possible, or must be given so that the reasoning results are within the tolerance of the problem.

On the other hand, possibility is an ordinal scale of uncertainty in spite that the value is numerical. In other words, possibility has the qualitative nature, while probability is a quantitative scale of uncertainty.

Yamada [7], [9] proposed a method to calculate the possibility of multiple causes occur at the same time using the possibility theory. In addition to the four-tuple \( < D, M, C, M^+ > \), the method needs prior possibilities distribution \( \{\Pi(d_j), \Pi(C_j | d_i)\} \) of diseases and conditional causal possibilities distribution \( \{\Pi(c_{ij} | d_i), \Pi(c_{ij} | d_i)\} \) to calculate possibilities of hypothesis under \( M^+ \) condition, namely \( \{\Pi(E_k | M^+), \Pi(e_k | M^+)\} \). \( c_{ij} \) is a causation event that means disease \( d_i \) causes symptom \( m_j \). In general \( \Pi(m_j | d_i) \geq \Pi(c_{ij} | d_i) \) holds. There are studies which assert that possibility of causation recognized by human is not \( \Pi(m_j | d_i) \), but \( \Pi(c_{ij} | d_i) \) [12].

When symptoms \( M^+ \) are observed, the possibility that diseases in explanation \( E \) cause the symptoms can be calculated by

\[
\Pi(E | M^+) = \begin{cases} 
\Pi(M^+ | E) \land \Pi(E), & \text{if } \Pi(M^+ | E) > \Pi(M^+ | E) \land \Pi(E), \\
1, & \text{otherwise},
\end{cases} \tag{4}
\]

where \( \land \) means minimum in possibility calculation. Note that \( \Pi(E) \) represent the possibility that all diseases in \( E \) arise, and not the possibility that just one in \( E \) arises in the equation. See [2,7] for details for the calculation.

**C. Outline of clinical reasoning**

The outline of clinical reasoning is explained here.

A clinician is supposed to input all symptoms obtained during the consultation such as the patient’s complaints, the
results of physical examination, etc. into the electronic medical chart. Then, the system derives new explanations of the symptoms given so far using the sequential algorithm of abductive reasoning, calculates their possibilities using eq. (4), permutating them in the order of possibilities, and show them to the clinician, every time a new symptom is given. Therefore, he/she can conduct the consultation or diagnosis, as seeing the possible diseases and their possibilities. Typically, he/she decides which information should be obtained through the medical examination, referring to the reasoning results on the display. This process is just the sequential reasoning discussed as the first requirement.

As for the third and fourth requirements -- handling of multiple diseases assumption and relief of knowledge acquisition by using causal knowledge, it is evident the abductive reasoning employed in the system can satisfy them. In the rest of the section, the relation between possibility theory and the rare serious disease problem is discussed.

Possibility is an ordinal scale of uncertainty when Hisdal’s [11] definition of conditional possibility is used, while Probability is a ratio scale of uncertainty. Actually, mathematical operations used in possibilistic reasoning are almost maximum and minimum, which correspond to arithmetic sum and product, respectively in the case of probability theory.

The ordinal calculation of possibility can prevent the problem of eliminating rare serious diseases from the candidate list. In the case of probability, the final probability of a very rare disease may become extremely small mainly due to its very small prior probability. However, in the case of possibility, the final possibility of the very rare disease \( d_i \) does not become less than the prior possibility \( \Pi(d_i) \), when \( \Pi(d_i) \) is very small and less than other \( \Pi(d_j) \) and \( \Pi(\bar{d}_i | E_i) \). Therefore, the problem could be solved, if all the possibilities are classified into several levels and excessively small prior possibility is not used.

V. OUTLINE OF DIAGNOSIS SUPPORT SYSTEM

A. System Overview

Based on the proposed model, we develop a medical diagnosis system to support clinical reasoning. The system provides a build-in database of diseases and symptoms, which are formatted in ICD-10 list. When a clinician develops a knowledge base, what he/she must do is just to link the target diseases with their symptoms and to give their possibilities, i.e. \( \{ \Pi(d_i), \Pi(\bar{d}_i) \} \) and \( \{ \Pi(c_i | d_i), \Pi(\bar{c}_i | d_i) \} \).

In the daily practice, the clinician inputs the observed symptoms into the system, and the system returns the possible disease hypotheses. Then he/she views the details of each hypothesis to plan the following diagnosis.

When the next observation or a symptom is found, the clinician will add the observed symptom to narrow down the possible diseases. This process will be repeated until the clinician conform the hypothesis.

In this system, the clinician can input not only observed symptoms but also the negation of symptoms, and even unknown state of symptoms. The denied symptom can be used to eliminate diseases which necessarily cause the symptom. When the state is unknown for a symptom, the knowledge about the symptom is ignored.

B. System Evaluation

To evaluate the usefulness of the proposed system in a clinical site, a practical evaluation by a physician was done. The focus of evaluation is the effectiveness of the four

<table>
<thead>
<tr>
<th>DISEASE NAME IN EXPERIMENT</th>
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<tbody>
<tr>
<td>1. Angina Pectoris</td>
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<tr>
<td>5. Arrhythmia</td>
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<tr>
<td>7. Aortic Dissection</td>
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<tr>
<td>9. Valvular Disease of the Heart</td>
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<tr>
<td>11. Hypertrophic Cardiomyopathy</td>
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<tr>
<td>15. Acute Pericarditis</td>
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<tr>
<td>17. Myocarditis</td>
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<td>19. Pulmonary Embolism</td>
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requirements described in section 4. The experiment was done for the diagnosis of the diseases related to chest pain with cooperation of the Fukushima University Physical Education and Health Care Center. Table 1 shows the diseases considered in the evaluation.

The knowledge base was constructed on the assumption that the patient layer was a university student. It has 20 kinds of diseases in Table 1 and 60 kinds of symptoms. It took only 20 minutes to setup all the information with the system.

In a test case, the chest pain is input as an initial symptom. So, \( M^+ \) is \{chest-pain\}. In this case, only one symptom is observed, therefore the explanations are limited to a single disease only. The System calculates the possibility \( P(E_k | M^+), P(E_k | M^-) \) for all single diseases registered, and sorts them in the order of possibility. In this test, when \( M^+ \) is \{chest-pain\}, the disease with the highest possibility is hyperventilation syndrome with \{1.0, 1.0\}.

The diseases with the lowest possibility are Myocardial Infarction, Valvular Disease of the Heart, Pulmonary Embolism and Chronische Cholezystitis, whose possibility is \{0.1, 1.0\}.

For example, suppose that the patient has an additional claim, cold sweat. In this case, \( M^+ \) becomes \{chest-pain, cold-sweat\} and the diagnosis result is Pneumothorax with \{1.0, 0.4\} and Myocardial Infarction with \{0.1, 1.0\}. It means this system support the sequential reasoning. Then, the clinician asks if the patient has dyspnea or not. If he/she has dyspnea, the sequential reasoning concludes two explanations; Pneumothorax with \{1.0, 0.4\} and \{Myocardial Infarction, Pulmonary Embolism\} with \{0.1, 1.0\}. The second explanation shows that Myocardial Infarction and Pulmonary embolism may occur at the same time, though its possibility is small. We can understand that system can handle multiple disease assumption and reason the rare serious disease problem.

VI. CONCLUSION

The paper proposed a clinical reasoning model that satisfies four important clinicians’ needs: sequential reasoning, rare serious disease problem, handling multiple disease assumption and knowledge acquisition problem. Based on the proposed model we develop a medical diagnosis support system to check the validity of the model. We find that the proposed model is effective to support clinical reasoning.

The next aims are to include patient’s state of health, living conditions information as knowledge-based. Then evaluate the system in medical institute or hospital.

REFERENCES