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An Intelligent Human-Computer Interface for Medical Diagnosis Systems

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Abstract

The first process in medical diagnosis is to gather useful patient data from physical examination. How to capture proper, correct and complete morbidity from a consultation is a very difficult task. This paper proposes an intelligent human computer interface to alleviate the problem. It includes a hypermedia human-machine interface, a common sense and past Q&A repository, and a user assistant. The hypermedia interface provides a friendly human body image map for the clinician to easily enter patient data. It guides the user to input relevant patient's data according to his level of proficiency with the help of the medicine-related common sense and past Q&A scenarios. The user assistant supports the hypermedia interface by determining the proficiency level of the user, checking the completeness, consistency, and rationality of the input data, and transforming the patient data into a complete patient record. This intelligent system can help all levels of users to correctly and easily gather high-quality patient's data.

1. Introduction

Diagnosis is the first process for medical treatment. A clinician needs to collect patient's information, such as subjective findings, objective findings, pathology examination, and laboratory testing in order to make correct judgement [1]. The subjective findings depict the chief complaints of the patient. The objective findings record the investigation conducted by the clinician. Table 1 illustrates the main subjective and objective findings of a patient record. The testing data refer to the information from laboratory tests. It normally takes years of training and practice for a physician to be able to correctly collect these data based on his understanding of the relationships among symptoms, diseases, and testing data. This worsens if the related etiology is hard to discern. Thus, the first difficulty for a physician to do correct diagnosis is the identification of the most relevant features from either overwhelming symptoms and laboratory data or incomplete data. Although computer-aided medical diagnosis systems have been proposed to help the diagnosis process [3, 11, 9, 11], they require the experienced user to input proper and correct data. The correctness of their diagnoses is thus heavily dependent on the quality and correctness of the input data. They leave the problem of identification of relevant investigation on the patient to the user. Providing an intelligent, flexible, and user friendly interface to collect these data from the users of different proficiencies thus becomes the most significant and influential task.

Table 1 Subjective and objective findings

Subjective findings	*Objective findings*		
Age	Present illness	Temperature	Pulse rate
Sex	Repository rate	Blood pressure	Consciousness
Family history	HEENT (Head, Ear, Nose, and Throat)	Neck	Heart
Personal history	Thorax & lungs	Breast	Abdomen
Chief compliant	Extremity	Urinary	Neurologic

In this paper, we propose an intelligent human computer interface (IHCI) that can collect useful data to support the diagnosis task. It contains a knowledge base of medicine-related common sense [7], a repository of transaction records, and a method to select relevant features [2]. The medicine-related common sense characterizes morbidity and the relationships between symptoms and diseases [4, 6]. The transaction records remember the interaction scenarios of the users. The relevant feature selection method selects the features that are relevant to the given symptoms and diseases. Integrating these capabilities empowers the user interface with the following features. First, with the help of the medicine-related common sense and transaction repository, it can properly discriminate the proficiency level of the user and guide him to effectively capture problem features accordingly. Moreover, the feature selection method can help pinpoint and later on eliminate irrelevant features from the patient data, and thus narrow down possible disease types. In summary, the interface not only can reduce the time in the question-and-answer process but also increases the reliability of the acquired patient data.

2. System Architecture

Fig. 1 shows the IHCI architecture. It contains three modules, i.e., a hypermedia human-machine interface, a knowledge and information repository, and a data assistant. The hypermedia human-machine interface allows the clinician to interact with the system via a friendly human body image. The knowledge and information repository stores the medicine-related common sense and the Q&A scenarios. The former refers to the common sense of an average doctor. It is used to determine the rationale of the objective findings and laboratory tests. It also fuzzily relates possible disease types to patient's morbidity. The latter organizes all the questions that were previously asked. It serves as a good example of how to fill in missing details for a given question once the question has been answered before. The data assistant uses the repository to identify the professional level of the user based on fuzzy theory [10], provides the user with proper help functions, and suggests related answers to the user. It also singles out relevant features for possible disease types. Fig. 2 summarizes its overall operation. The following detail each module.

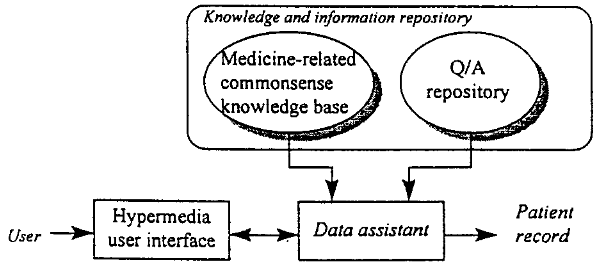

Fig. 1 Architecture of the intelligent human-computer interface

1. Request the user to input the patient's subjective and objective findings.
2. Check the rationality of the input data.
3. Make preliminary hypotheses about possible disease types.
4. Determine the user's proficiency level.
5. Interact with the user according to his proficiency level to get more data.
6. Check whether all of the fields were filled? If not, go back to step 3.
7. Check whether the input data is rational and complete? If not, warn the user and go back to step 3.
8. Produce a complete patient record.

Fig. 2 Overall operation of IHCI

3. Hypermedia Human-Machine Interface

The hypermedia human-machine interface displays a human body image with visible organs for entering patient data (Fig. 3). The image classifies diseases into eleven disease types, named after related organs, i.e., cardiology, respiratory, hematology, GIH (gastric, intestine, and hepatology), nepolasm, urology, immune diseases, infectious diseases, endocrine, neurology, and miscellaneous [5, 7]. By clicking on an interested organ, a clinician gets the associated pop-up question screen. He then enters the patient's subjective and objective findings, which will be sent to the data assistant to check for rationality, to establish a diagnostic hypothesis, and to determine the profession level of the user. The subsequent interaction style will then depend on the user's professional level. Fig. 4 exemplifies the interaction screen for an expert level of user. It expects the user can independently complete all the blank fields. If the user is determined to be a novice, the interface will change to provide suggestions of possible past solutions to help him answer questions. When some of the relevant features are omitted, the interface will be instructed by the data assistant to ask the user for the data. By this way, the hypermedia interface can provide different user screens along with assistant functions for the user according to his proficiency, which facilitates the patient's data gathering process.

Fig. 3 Hypermedia medical user interface

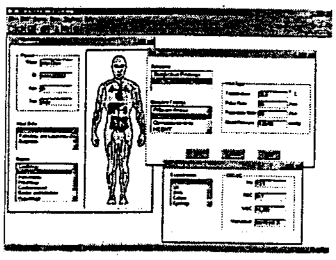

Fig. 4 Interaction style for an expert level of user

4. Knowledge and Information Repository

First, the medicine-related common sense contains knowledge about the model of a human body, typical relationships between symptoms and diseases, fundamental physical examination procedures, basic diagnosis methodology and procedures, basic morbidity of various diseases, medical decision processes, and basic diagnosis-related principles and concepts. We treat this as the commonsense of an average doctor. Table 2 exemplifies the relationships between 4 symptoms and 11 disease types. It says, for example, symptom "cough" is "highly" relevant to the "Respiratory" disease (disease type 2), but is independent of hematology (3) and endocrine diseases (9). These relationships will help to determine the proficiency level of the user according to his answer data. Note that this usage of common sense is quite specific compared with CYC [8].

Table 2 Relationships between symptoms and disease types

	1	2	3	4	5	6	7	8	9	10	11
Cough	SE	H	N	SE	F	N	SE	SO	N	SE	N
Dyspnea	H	H	N	N	H	N	N	SO	N	SE	SE
Edema	SO	N	N	SE	N	SO	N	N	N	N	H
Hempotysis	SO	N	SE	N	SO	SO	SO	H	SO	N	H

Legends:

N: Never, [0, 0.2],
SE: Seldom, [0.1, 0.4],
SO: Sometimes,[0.3, 0.6],
F: Frequently, [0.5, 0.8],
H: Highly, [0.7, 1.0]

1: Cardiology 2: Respiratory
3: Hematology
4: Gastric, Intestine, & and Hepatology
5: Neoplasm 6.Urology
7: Immune 8: Infection
9: Endocrine 10: Neurology
11: Miscellaneous

The Q&A repository, containing the past Q&A scenarios, works with the help of a housekeeping engine, which stores, calculates, selects, and aggregates the data relevant to those the user answers. It conducts statistics on the answered items in the repository and produces proper recommendation to help determine whether to ask further questions or not.

5. User Assistant

The user assistant is the major component of IHCI. It conducts the following tasks. First, it determines the proficiency level of the user, and instructs the human-machine interface to provide proper help functions for the user accordingly. It classifies the users into five levels, i.e., experts, seniors, juniors, novices, and amateurs. An expert is expected to contain profound expertise in the fields of clinical diagnosis, morbidity of diseases, and pathology. A senior is a physician with fairly strong clinical experience in clinical diagnosis. A junior is a doctor with less clinical experience. A novice is like a resident doctor or medical student. Finally, an amateur is the one who is interested in medicine but not conducting the profession in the field. The assistant categorizes the user by evaluating the *accuracy, usefulness, direction,* and *reliability* of his answer data. We define the professional measurement (η) of the user by the following equation.

$$\eta = f(A, U, D, R) = A*W_A + U*W_U + R*W_R + D*W_D, \quad (1)$$

where A, U, R D are the measurements of accuracy, usefulness, reliability, and direction, respectively, to be detailed below. W_A, W_U, W_R, and W_D are the respective weights, which are defined differently for each user's professional level. By this, we can properly reflect the biased weighting system at each proficiency level. Table 3 illustrates the expected measurements and the associated weights of each user level. Fig. 5 summarizes the help functions for different levels of users.

Table 3 User proficiency level discrimination table

	Expert	Senior	Junior	Novice	Amateur
Accuracy (W_A)	High (0.25)	High (0.225)	Mid (0.2)	Low (0.2)	Poor (0.15)
Usefulness (W_U)	High (0.25)	High (0.225)	Mid (0.2)	Low (0.2)	Poor (0.15)
Direction (W_D)	High (0.25)	Mid (0.2)	Mid (0.15)	Low (0.15)	Low (0.1)
Reliability (W_R)	High (0.25)	Mid (0.2)	Mid (0.15)	Low (0.15)	Poor (0.1)

1. **Expert:** directly fill data into the table.
2. **Senior:** hint the user with relevant features and provide guidance about the problem (directly fill data to the relevant fields).
3. **Junior:** provide question/answer auxiliary functions and ask related questions about the disease type in terms of questions and answers.
4. **Novice:** provide question/answer auxiliary functions (and rank previous similar answered data), ask related questions about the disease type, and explain "why" the question and "how" to reach the solution.
5. **Amateur:** provide question/answer auxiliary functions (and rank previous similar answered data), ask related questions about the disease type, and finally give a rough diagnosis.

Fig. 5 Different levels of user help functions

The accuracy factor, A, measures whether the input terminology falls in the pre-defined possible morbidity or not. It unfolds the medicine literacy of the user. A is calculated below.

$$A = 1 - \frac{\sum_{i=1}^{n} |x_i - y_i|}{n}, \quad (2)$$

$$\text{where } |x_i - y_i| = \begin{cases} 1, & if \quad x_i \subset y_i \\ 0, & if \quad x_i \not\subset y_i \end{cases}$$

x_i represents the input feature value i, y_i represents the corresponding pre-defined terminology, and n is the numbers of features.

The usefulness factor, U, represents the effectiveness of the input data. It unfolds the investigation ability of the user on physical examination, defined by

$$U = \frac{k}{t}, \quad (3)$$

where k is number of entered abnormal attributes and t is number of all features.

The direction factor, D, represents the relevance degree between the patient data and the diagnostic hypotheses of disease types. It reveals how strong the answered data converges to some disease types, defined by

$$D = \max_i (RF_i) \quad (4)$$

$$RF_i = \frac{\# K_{ij}}{t}, \quad (5)$$

where RF_i is relevance degree of disease type i, $\#K_{ij}$ is the number of relevant feature j in disease type i, and t is the total number of relevant features in disease type i.

The reliability factor, R, represents the maximum certainty of the preliminary disease hypotheses, computed by

$$R = \max_j \left(\frac{1}{n} \sum_{i=1}^{n} F_i * P_{ij}\right), \quad (6)$$

where F_i is the representative fuzzy value of feature i and P_{ij} is the relationship degree between feature i and disease type j, as shown in Table 2, and n is the number of features in disease type i.

The second thing the data assistant does is to check the input data for completeness, consistency, and rationality. First, if the user cannot provide answers (i.e., incomplete data), it will invoke the Q&A repository. From the set of possible answers returned by the Q&A repository, it then chooses the best one for the user. If any input data is vague or in conflict with others (inconsistency), it will ask the clinician for clarification, which reduces the uncertainty of the patient data. It also analyzes the rationality of the input data with the help of the medicine-related common sense. Take the normal patient temperature as a common sense example, which is in the range between 30 and 41 (°C). If the input temperature is out of this rage, the data assistant will warn the user of this irrationality.

After the input data is completed, the data assistant transforms it into a fuzzy representation. Fig. 6 exemplifies the fuzzy representation for temperature. The user assistant is now doing its third task by hypothesizing preliminary possible disease types according to the subjective and objective findings with the help of medicine-related common sense, such as Table 2. These hypotheses allow the data assistant to compute relevant features using the relevant feature selection algorithm (Fig. 7). These relevant features serve as the focused questions for the user to enter answers.

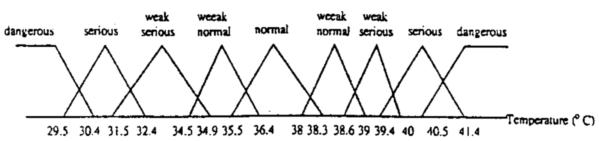

Fig. 6 Example of temperature's fuzzy partition

1. Initialize a relevant feature set.
2. Compute the relevance of each feature:
   Degree of the feature * Relationships value to the disease type
3. Add all of the features with relevance value higher than the threshold into the relevant feature set.
4. Refine the relationships if the above relevant feature is very strong.

Fig. 7 Relevant features selection algorithm

The data assistant finally produces two categories of output data. One is the information for controlling the graphic user interface, supplemented with the data from the Q&A repository and the KA-related commonsense. The other contains the patient record enhanced from the user input data, the professional level of the user and the query data. Fig. 8 illustrates the patient record.

Patient's model

- Subjective findings:
  - ✓ Age: 51
  - ✓ Sex: male
  - ✓ Marriage: No
  - ✓ Family history: Normal
  - ✓ Personal history: Smoking
  - ✓ Chief complaint: Chest pain, Cough,
- Objective findings:
  - ✓ Present illness: Sputum cruentum, Vertigo, fever
  - ✓ Physical examination:
    - A. Vital sign
      - 1. Temperature: 39.8 (℃), Serious
      - 2. Pulse rate: 90 (/min), Normal
      - 3. Repository rate: 20 (/min), Normal
      - 4. Blood pressure: 120/80 (mmHg), Normal
    - B. Consciousness: Normal
    - C. HEENT (Head, Ear, Nose, and Throat): Normal
    - D. Neck: Normal
    - E. Heart: Normal
    - F. Thorax and lungs: thorax unbalanced (right side)
    - G. Breast: normal
    - H. Abdomen: Normal
    - I. Extremity: Normal J. Urinary: Normal
    - K. Neurologic: Normal
- Pathology and Laboratory data:

1. CBC-DC:
   A. Hb: 13.5 B. RBC: 417 C. WBC: 16,350 D. Hematocrit: 60/70 (46.2)
2. UA:
   A. Urinary: Normal
3. SMA:
   A. Sugar: 150 B. BUN: 25 C. Na: 136 D. K: 4.8
   E. Cl: 94 F. A/G: 3.0/2.8
   G. Alk-P(BU): 13.3 H. GOT: 25 I. GPT: 17 J. Bil (D/T): 0.5/1.0 K. CCF: Negative
   L. Mucoprotein: 215 M. Effusion protein: 7800 (mg)
4. Culture
   A. Sputum: Negative B. Effusion: Negative
5. Cytology
   A. Effusion: Cancer

- Imaging:

1. Chest x-ray: Pleural effusion 2. EKG: Normal

Fig. 8 Output patient record

6. Conclusions

We have described an intelligent human-computer interface for medical diagnosis. It is equipped with a friendly hypermedia user interface, which supplies different interaction styles and helping functions according to the level of the user proficiency in the medical field. It is equipped with a repository that contains the medicine-related commonsense and the dialogues of past user interactions. The former includes the human body model, typical relationships between symptoms diseases, and basic diagnosis-related principles and concepts. The latter properly organizes all the past Q&A scenarios, conducts statistics on the answered items in the repository, and produces proper answer suggestions for the user. Finally, the system is equipped with a user assistant to support the hypermedia interface. The assistant can discriminate the proficiency levels of the users; check the completeness, consistency, and rationality of input data; and make preliminary hypotheses from a patient record. This intelligent interface possesses the following features. It solves the problem of unreasonable input data with the help of medicine-related commonsense. It provides different interaction styles to the users of different backgrounds by properly categorizing the medical literacy of the users from the quality of the investigated data. It is able to guide the user to focus on specific disease types by establishing preliminary hypotheses from the input data. In a word, the system can help all levels of users to easily gather high-quality patient's data. This system is currently implemented as a front-end to a medical diagnosis system under construction.

7. Acknowledgements

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