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An Application of Soft Computing to RETS: Rheumatic Evaluation and Treatment System by Oriental Medicine

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Abstract: *In this paper, we present an application of soft computing into an expert system RETS: Rheumatic Evaluation and Treatment System by Oriental Medicine (OM). Inputs are severities of observed symptoms on patients and outputs are a diagnosis of rheumatic states, its explanation and herbal prescriptions. First, after using fuzzy inferences, RETS diagnoses the most suitable rheumatic state in which the patient appears to be infected and shows explanations. Next, based on prescriptions for rheumatism learned by neural networks from skilled OM physicians and OM text books, RETS gives an oriental prescription written in suitable herbs with reasonable amounts. Finally, we describe evaluations and restrictions of RETS, and then describe our future work.*

Keywords: expert system, decision support system, neural networks, fuzzy inference

1. Introduction

Rheumatism is an arthritis disease widespread in all Vietnamese population groups, unfortunately influencing socioeconomic aspects of Vietnam. It accounts for 15% of all soft tissue diseases. The most popular rheumatic type, joint degeneration, accounts for 10% [1]. In Vietnam, therapeutic ways for rheumatism are physical methods, anti-inflammatory and oriental medicine (OM). Among them, OM is an indispensable part because it has fewer side-effects than western medicine and gives good treatment results. Besides, herbal prescriptions are easy to find and relatively cheap in comparison with western drugs. The number of Vietnamese patients treated by OM is about 50 %.

The accurate diagnoses have an important role in disease treatments. Building a successful expert system such as RETS based on knowledge from skilled OM physicians will help moderate evaluation in rheumatic diagnoses which tend to be subjective. It will indirectly help physicians to provide the right treatments to the right patients, thus improving the quality of the health care services as a whole. It also help qualified and experienced physicians in OM to maintain and share their profound knowledge with colleagues and to assist medical students or young physicians, especially those living and working in rural areas.

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2. Expert System (ES)

In the last recent decades, the advent of the computer has greatly stimulated developments of ES which performs the roles of a specialist or carry out some works requiring specific expertise. There were many domains in which ES has been successfully applied, such as medicine [2-4], geology [6], chemistry [7] and business [8].

According to OM, rheumatism consists of 12 disease states and 32 mainly typical clinical symptoms. The number of herbs for rheumatic treatment is 63 [11]. Based on severities of observed symptoms on patients, doctors diagnose and classify states of rheumatism, then give corresponding herbal prescriptions with reasonable amounts in grams. Fig. 1 shows the process of diagnosis and prescription of rheumatic treatment by OM doctors. Such a process can be suitably assisted with an ES as shown in Fig. 2 [9]. Functional parts of Fig.2 are as follows:

Knowledge Acquisition: Survey symptoms, explanations, sample prescriptions and training data.

Knowledge Base: Consists of symptoms, inference rules, training data and explanations.

Fuzzy Inference: Checks rules, calculates weights and gives proper rheumatic state. Inputs to the fuzzy inference are severities of observed symptoms and rules, and one output that is the most serious of the rheumatic state that the patient has.

Neural Network: Gives reasonable amounts of herbs in treatment prescriptions. Inputs to NN are also severities of observed symptoms, and outputs from

NN are coefficients of herbal amounts in [0, 1].

Interface: Obtains symptoms and their severities from users and shows results written in infected rheumatic states and appropriate treatment prescriptions.

Explanation: Helps users understand OM, rheumatism, ES and explains results from RETS.

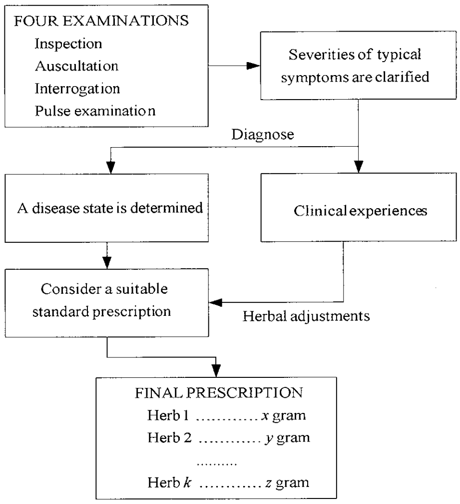

Fig. 1. Diagram of diagnosis and prescription of rheumatic treatment by OM doctors

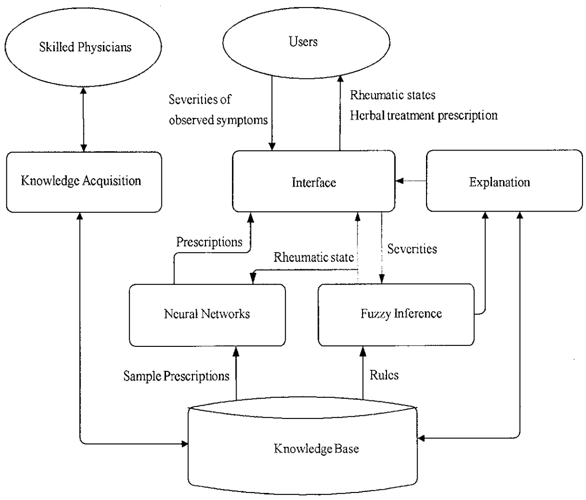

Fig. 2. Structure of ES for RETS

3. Fuzzy Inference

In OM, physicians usually give herbal prescriptions basing on severities of clinical symptoms such as high fever, slightly numbed joints, moderately yellow urine etc. These fuzzy expressions of symptoms make it unsuitable for traditional quantitative approaches to build OM expert systems. Fuzzy sets, known for their abilities to deal with vague variables using membership functions rather than with crisp values, proved to be one of the most powerful approaches to resolve the above problem. They also enable developers to use linguistic variables and build a friendly user interface. OM physicians usually explain diagnosing procedures with such expressions as "this patient has these typical symptoms with these severities, so I prescribe those herbs with those weights." These expressions can be represented naturally in IF-THEN fuzzy rules. In addition, fuzzy rules can give expert-like explanations, and make it easier for doctors to understand the ES.

So far, based on fuzzy logic many practical applications in medicine have been built, including OM [2] and rheumatic disease with western medicine [4].

In the first stage of RETS, fuzzy inference is used to decide which rheumatic states the patient has. Then in the second stage, the fuzzy severities of symptoms are put into a corresponding neural network to get an appropriate prescription.

3.1. Symptom and Rule Expressions

Suppose that rheumatism has $m = 32$ clinical symptoms, $l = 12$ rheumatic states. A rheumatic state is determined by n clinical symptoms. Since all of the clinical symptoms will not appear in one rheumatic state, the value of n may vary depending on each state, for example $n = 16$ for state 1, $n = 13$ for state 2, and so on.

Let $S^O = (S_1^O, S_2^O, ..., S_m^O)$ be the set of observed symptoms on a patient where S_i^O is a fuzzy proposition representing a symptom.

Let $H = (H_1, H_2, ..., H_l)$ be the set of the rheumatic states.

Let $S^{R_j} = (S_1^{R_j}, S_2^{R_j}, ..., S_n^{R_j})$ be a set of symptoms in the premise of rule $R_j (j = 1, 2, ..., l)$ where R_j is generally described in the following form:

$$\begin{aligned}&\text{IF } S_1^{R_j} \textit{ and } S_2^{R_j} \textit{ and} \ldots \textit{and } S_n^{R_j}\\&\text{THEN } \textit{the rheumatic state is } H_j .\end{aligned} \quad (1)$$

Rule form (1) means there are n symptoms in premise of the rule. Symbol $S_1^{R_j}$ can be understood as *Symptom* 1 in premise of rule R_j . j is rule number.

Let the two following fuzzy values in S_i^O and $S_i^{R_j}$ be defined:

$\mu_{S_i^O} \in [0,1]$: truth value of S_i^O given by doctors when diagnosing. $\mu_{S_i^O} = 1$ means S_i^O clearly appears on the patient, $\mu_{S_i^O} = 0$ means S_i^O does not appear on the patient, and $0 < \mu_{S_i^O} < 1$ means S_i^O appears on the patient with the severity $\mu_{S_i^O}$.

$\mu_{S_i^{R_j}} \in [0,1]$: importance value of $S_i^{R_j}$ for rheumatic state H_j given by skilled doctors via survey in advance, where:

$$\sum_{i=1}^{n} \mu_{S_i^{R_j}} = 1 \qquad (2)$$

$\mu_{S_i^{R_j}} = 0$ means $S_i^{R_j}$ has absolutely no affect on H_j , $\mu_{S_i^{R_j}} = 1$ means $S_i^{R_j}$ is the only symptom affecting H_j , and $0 < \mu_{S_i^{R_j}} < 1$ means $S_i^{R_j}$ affects H_j with certainty factor $\mu_{S_i^{R_j}}$.

The importance values are used because different symptoms affect rheumatic states differently. For a rheumatic state, some symptoms are more important than the others while some do not. For example, symptom "*Afraid of wind*" is the most important for rheumatic state 1, but this symptom has no effect on rheumatic state 3.

The sum in Eq. (2) equals 1, which means the maximum belief degree of the premise of rule R_j is 1. It is also a boundary, so experienced doctor should consider the importance values within this boundary, avoiding many doctors freely express the importance of symptoms with their own view.

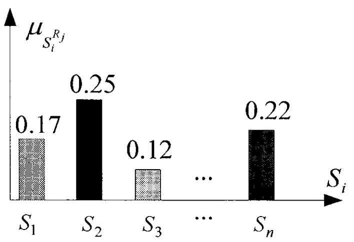

Fig. 3. An example of importance values of symptoms in premise of a rule

Fig. 3 shows an example of importance of symptoms in the premise of a rule. In this case, symptom S_2 is more important than the others. S_2 affects R_j with the certainty factor $\mu_{S_2^{R_j}} = 0.25$.

3.2. Fuzzy Inference Process

If an observed symptom S_i^O is found in the premise of rule R_j , actual effect of symptom S_i^O in premises of R_j (denoted by $w_{S_i}^j$) is calculated as:

$$w_{S_i}^j = \mu_{S_i^O} \otimes \mu_{S_i^{R_j}}. \quad (i = 1, 2, ..., n) \qquad (3)$$

where $\otimes$ is a t-norm operator, $x \otimes y = (x \times y)$ in RETS.

If symptoms S^{R_j} of R_j match observed symptoms S^O , conclusion weight of the rule R_j (denoted by w_{R_j}) is calculated as:

$$w_{R_j} = \underset{S_i \in \{S^{R_j} \cap S^O\}}{\oplus} w_{S_i}^j \qquad (4)$$

where $\oplus$ is a t-conorm operator, this t-conorm should be compatible with (1). $x \oplus y = (x + y)$ in RETS.

For example, rule R_5 has 6 symptoms: $S_1, S_2, \ldots, S_6$ in its premise. There are 11 symptoms observed on the patient: S_1, $S_2, \ldots,$ S_{11}. Suppose that these symptoms have severities and important values for R_5 as in the columns 2 and 3 on Tab.1. Then we have the actual effects ($w_{S_i}^5$) of each symptom in premises of R_5 as in the column 4, and the conclusion weight of the rule w_{R_5} as in the final cell of this table.

Tab. 1. Example of Calculating Rule Conclusion

Symptom	Importance value $\mu_{S_i^{R5}}$	Severities $\mu_{S_i^O}$	$w_{S_i}^5$
S_1	0.20	0.75	0.150
S_2	0.35	0.50	0.165
S_3	0.10	0.25	0.025
S_4	0.20	1.00	0.200
S_5	0.15	0.90	0.135
S_6	0.00	0.80	0.00
S_7	0.00	1.00	0.00
S_8	0.00	0.40	0.00
S_9	0.00	0.70	0.00
S_{10}	0.00	0.90	0.00
S_{11}	0.00	0.25	0.00
	$\sum \mu_{S_i^{R5}} = 1$	$w_{R_5} = \underset{S_i \in \{S^{R5} \cap S^O\}}{\oplus} w_{S_i}^5 = 0.675$	

Then RETS finds the most serious rheumatic state H^* which has the largest conclusion weight w_{R_k} among l rheumatic states:

$$H^* = \{H_k \mid w_{R_k} = \max_j w_{R_j}\} \qquad (5)$$
$$(j = 1, \ldots, l; \quad k \in [1,..,l])$$

For example, when the selected symptoms are as illustrated in Fig. 4, conclusion weights w_{R_k} of 12 rules are as shown in Fig. 5. In this case, the most serious rheumatic state is the state 4 with $w_{R_4} = 0.55$.

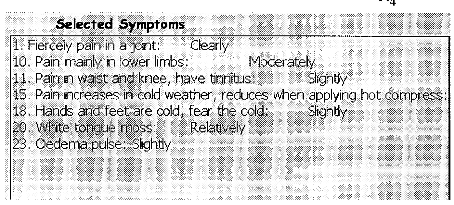

Fig. 4. Example of selected symptoms

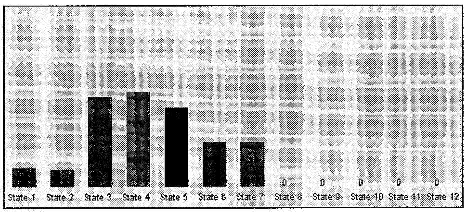

Fig. 5. Example of conclusion weights

Fig. 6 shows the diagram of the inference procedure. When the input symptoms are matched with one or more rheumatic states, system finds the most appropriate rheumatic state H^* corresponding with these inputs. If input symptoms are not matched with any rheumatic state, RETS gives an advice about the closest rheumatic state. In this case, patient may have diseases other than rheumatism.

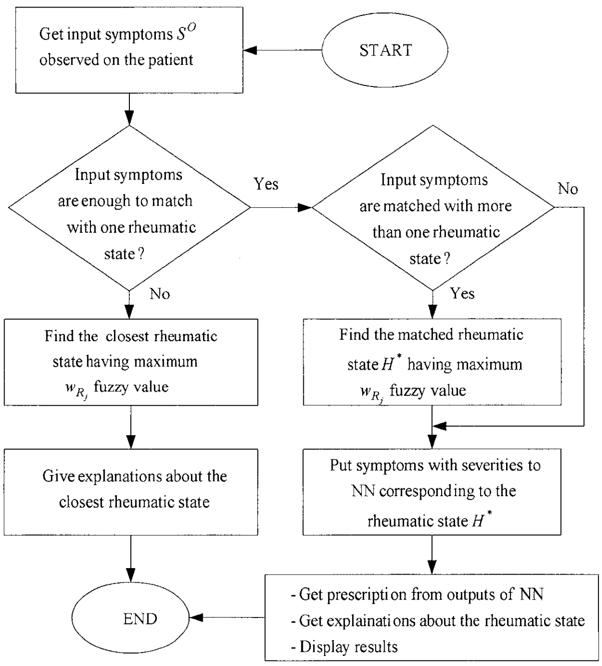

Fig. 6. Diagram of inference procedure

4. Neural Networks (NN) and Prescriptions

NN is a powerful technique to help doctors to analyze, model and make sense of complex clinical data across a broad range of medical application [5]. It enables intelligent systems to learn from experience, examples and clinical records, improving the performance of the systems over time. NN can generalize prescription rules and relations between symptoms and herbal amounts based on typical sample prescriptions collected from experienced doctors. After trained, NN can give suitable herbal prescriptions in accordance with the severities of symptoms observed on the patient.

After the fuzzy inference stage, NN as shown in Fig. 7, is used to adjust amounts of herbs in prescriptions. There are 12 networks corresponding with 12 rheumatic states. Input data to NN are state-specified symptoms S_i^O (i = 1,..., n) with severities $\mu_{S_i^O}$, and outputs are coefficients of amounts of herbs c_k (k = 1, 2, ..., p) in [0,1]. In RETS, NN often has n = 5 to 7 and p = 11 to 15.

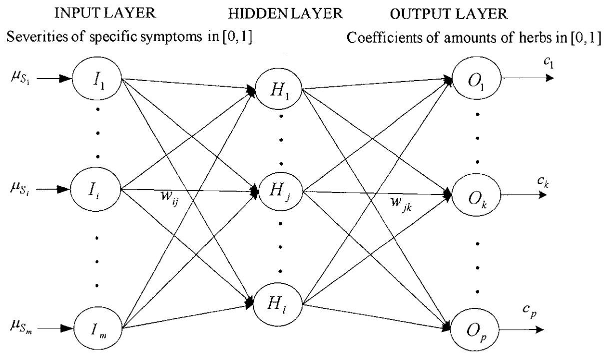

Fig. 7. One NN in RETS

The coefficients of amounts of herb c_k in training data are normalized as:

$$c_k = W_k^T / W^* \tag{6}$$

$$W_k^P = c_k \times W^* \tag{7}$$

where W_k^T is the amount of herb k in training data, W_k^P is actual amount of herb k in the prescriptive results, and W^* is the maximum amount of a herb in a prescription. In RETS, depending on each prescription, W^* = 20 or 60 grams.

5. Implementation

In the first phase, based on the text books, a preliminary survey and real rheumatic prescriptions from experienced doctors in Thaibinh OM College, we have assessed important fuzzy values of symptoms in rheumatic states, chosen standard prescriptions from the text books, clarified additional and equivalent herbs, selected specific symptoms that affected herbal adjustments, then generated 12,000 doctor-like prescriptions with combinations of severities of the state-specified symptoms using doctor-prescribing rules and linear methods with ranges of herbal adjustments. Training data for NN are the generated prescriptions together with 460 real rheumatic prescriptions from the experienced doctors.

With this training data and knowledge from the survey, we built RETS in Visual C# running on MS Windows 2000/XP. RETS has friendly interfaces with both languages of Vietnamese and English. NN adopted a sigmoid activated function. Adaptive learning and momentum term are also used. Figs. 8, 9 and 10 show the friendly interfaces of RETS for diagnosis, knowledge acquisition, prescription results and explanations, respectively.

6. Evaluation

Combining NN and fuzzy inferences, we can have a more powerful and effective ES with learning, reasoning and explaining capabilities for rheumatic treatments.

In our experiment, we randomly split training data into two parts of 70% and 30% and used the former for training and the later for testing. All of the nonlinear relations (real prescriptions and rules of prescribed herbs) as well as linear relations (ranges of herbal adjustments) were well learnt by NNs. Depending on the number of inputs and outputs, each NN can learn about 1000 prescriptions within an accuracy of 10^{-2} mean-square error for both training and testing data (equivalent to error of 0.1 gram for each herb).

In case of unknown inputs, RETS shows the fuzzy graph of infected rheumatic states, recommends the most proper state in which the patient seems to be infected and gives explanations by fuzzy inference, then shows the advised prescription with appropriate amounts of herbs by NN. Most of these prescriptions are completely compatible with the real prescriptions, prescribing rules and linear ranges of herbal adjustments in the training data.

7. Conclusions

We built RETS: Rheumatic Evaluation and Treatment System by OM, and showed the diagnosis system by fuzzy inferences and herbal prescription system by NN. Then we could confirm that RETS has high performance for diagnosis and prescription. Unfortunately, like other ESs often restricted to a narrow domain of expertise, RETS is developed for diagnosis of rheumatism diseases. It lacks much real knowledge of human philosophy [10]. If a patient has other diseases besides rheumatism, doctors cannot solely rely on this system since they do not have evidence to control potential effects of the herbal remedies on the other concurrent diseases. Hence, it is recommended that the system be used only for patients with rheumatism alone, not for those with other concurrent diseases.

Our future works are an adjustment of training data, addition of explanations, then re-evaluating the system in the real patients and comparing system's results with the doctors' diagnoses

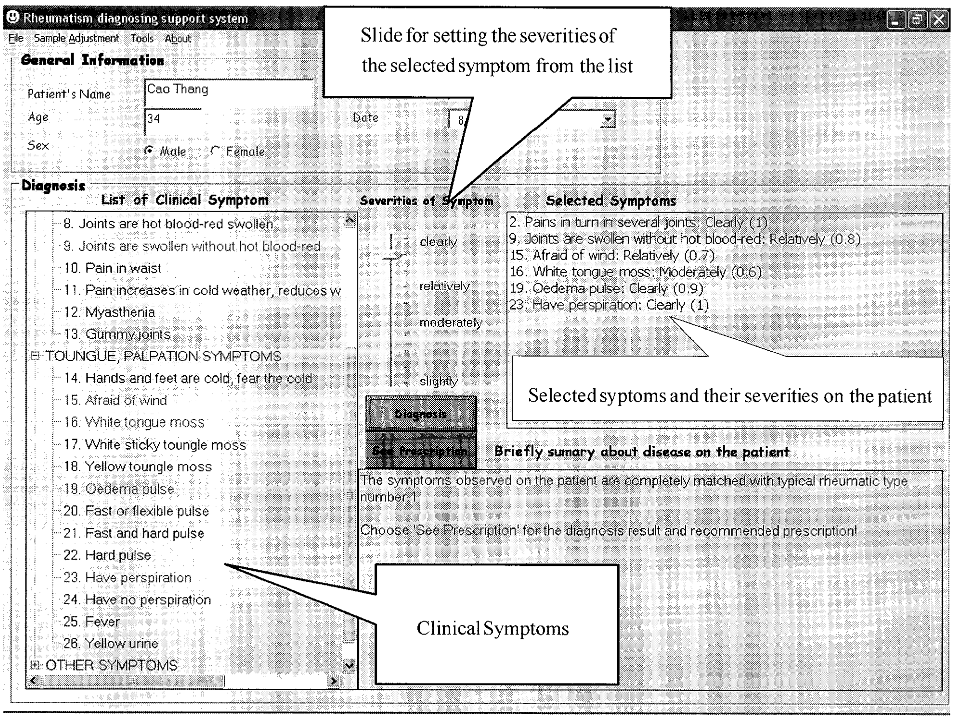

Fig. 8. Interface for diagnosis

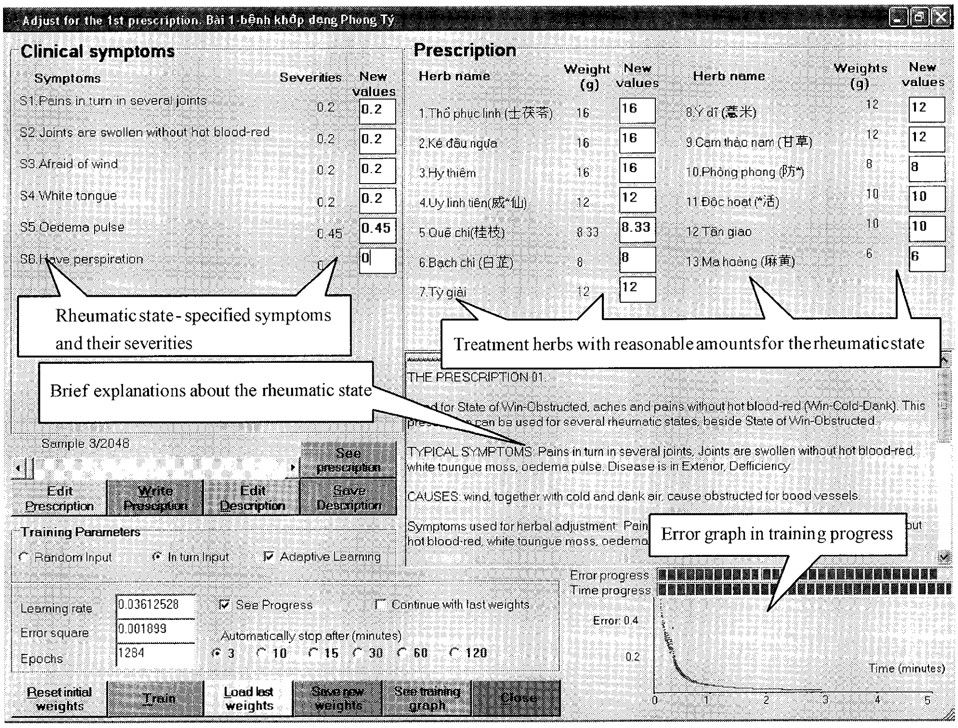

Fig. 9. Interface for knowledge acquisition

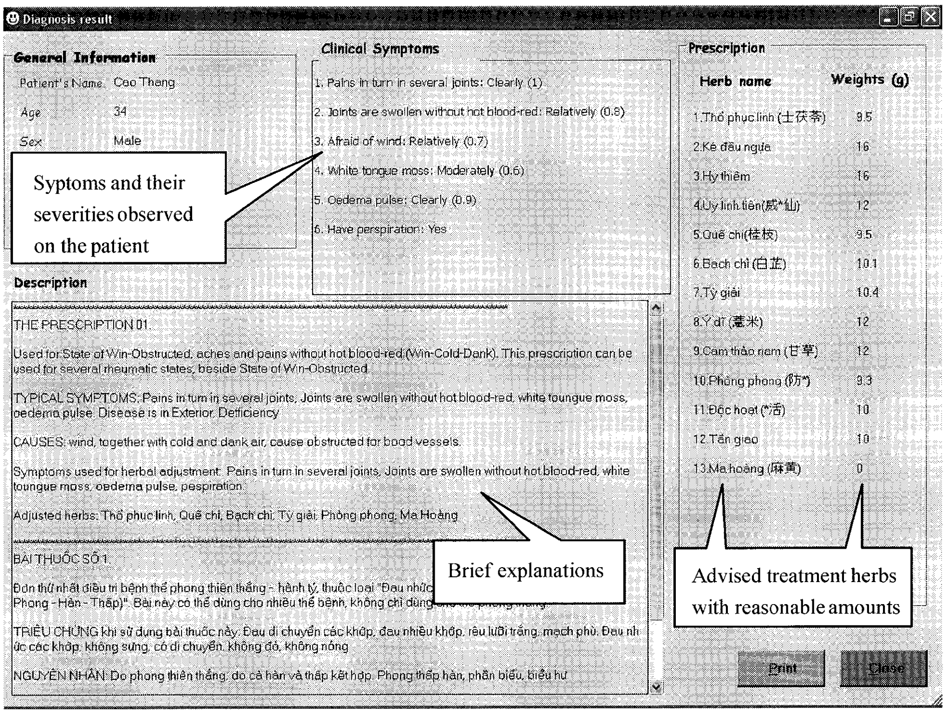

Fig. 10. Interface for prescription results and explanations

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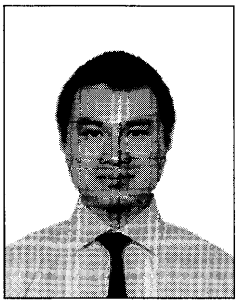

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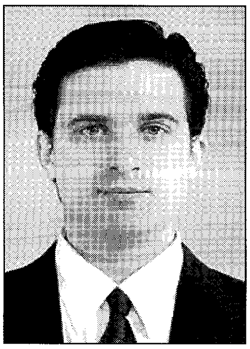

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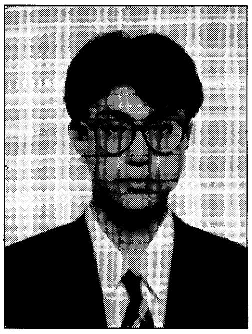

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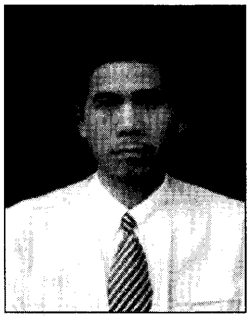

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