Pergamon

Expert Systems With Applications, Vol. 11, No. 3, pp. 351–360, 1996

0957-4174/96 $15.00+0.00

PII: S0957-4174(96)00050-4

Self-Integrating Knowledge-Based Brain Tumor Diagnostic System

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Abstract—*In this paper, we present a self-integrating knowledge-based expert system for brain tumor diagnosis. The system we propose comprises knowledge building, knowledge inference and knowledge refinement. During knowlege building, an automatic knowledge-integration process, based on Darwin's theory of natural selection, integrates knowledge derived from knowledge-acquisition tools and machine-learning methods to construct an initial knowledge base, thus eliminating a major bottleneck in developing a brain tumor diagnostic system. During the knowledge inference process, an inference engine exploits rules in the knowledge base to help diagnosticians determine brain tumor etiologies according to computer tomography pictures. And, a simple knowledge refinement method is proposed to modify the existing knowledge base during inference, which dramatically improves the accuracy of the derived rules. The performance of the brain tumor diagnostic system has been evaluated on actual brain tumor cases. Copyright © 1996 Elsevier Science Ltd*

1. INTRODUCTION

RECENTLY, EXPERT SYSTEMS have been successfully applied to many fields and have shown excellent performance. Expert systems provide sound expertise in the form of diagnosis, instruction, prediction, consultation and so on. They can also be used as training tools to help new personnel interpret data and monitor observations (Waterman, 1986). Developing a successful expert system requires, however, effectively integrating knowledge from a variety of sources, such as that from domain experts, historical documentary evidence, or current records, to construct a complete, consistent and unambiguous knowledge base (Baral, 1991; Gragun, 1987). For large-scale expert systems that generally cannot rely on a single knowledge source, the use of multiple knowledge inputs from many knowledge sources is especially important to ensure comprehensive coverage. Thus, integrating multiple knowledge sources plays a critical role in building successful expert systems. In this paper, we present a brain tumor diagnostic system that can integrate multiple knowledge sources to quickly build a prototype knowledge base. This prototype knowledge base then adapts itself according to inference results from the expert system, consequently improving the accuracy of the rules it derives.

The brain tumor diagnostic system (BTDS) consists of three main functional units: knowledge building, knowledge inference and knowledge refinement (Wang & Tseng, 1995). The knowledge-building unit includes three modules: machine learning, knowledge acquisition and knowledge integration. The machine-learning module maintains a variety of machine-learning strategies (Cendowska, 1987; Michalski, 1980; Mitchell, 1982; Quinlan, 1986) to induce knowledge from actual instances. The knowledge-acquisition module maintains

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different knowledge-acquisition tools that allow knowledge engineers to acquire domain knowledge from various experts (Kelly, 1955; Hwang & Tseng, 1990). The knowledge-integration module uses *evolutionary theory* to automatically integrate knowledge from multiple sources (which may be derived by knowledge-acquisition tools or machine-learning methods) into the initial knowledge base. The inference unit helps diagnosticians determine brain tumor etiologies according to computer axial tomography pictures. The knowledge-refinement unit uses a proposed knowledge-refinement method to modify the existing knowledge base during the inference process.

The remainder of this paper is organized as follows. The problem domain is introduced in Section 2. The architecture of the brain tumor diagnostic system is presented in Section 3. A knowlege-building unit is proposed in Section 4. A knowledge-inference unit is introduced in Section 5. A knowledge-refinement method is proposed in Section 6. The implementation of the brain tumor diagnostic system is presented in Section 7. Conclusions are given in Section 8.

2. THE PROBLEM DOMAIN

The field of brain tumor diagnosis is quite interesting and full of challenge since the brain is very complex and many causes of brain tumors are still unclear (Wills, 1982). Computer tomography (CT) is generally considered the most reliable diagnostic technique for locating and characterizing brain tumors. Nearly all intracranial lesions are detected using CT. The usual examination involves scanning the neurocranium in a series of parallel transverse "slices". The head is bent forward so that the sectional plane lies at an angle of 12° to the orbitomeatal lines (Fig. 1).

Each slice is 8 mm thick, so that 8–15 slices are usually sufficient to visualize the intracranial structures to be examined. A patient with a meningiomal tumor is shown in Fig. 2.

Normally, several stages are necessary for doctors to diagnose brain tumors. First, CT pictures of a patient's brain are analyzed and compared to determine the location and the density of the lesion. Next, the CT pictures are further analyzed to obtain data on calcification, degree of edema, shape of edema, degree of enhancement, type of enhancement, general appearance, size of mass, mass effect and bone change. After that, some possible brain tumors could be concluded.

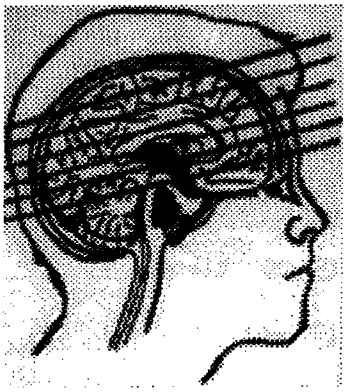


FIGURE 1. Positions of six standard CT scans.

FIGURE 2. An example of a CT picture.

The brain tumor diagnosis is still difficult for inexperienced doctors due to the inherent complexity of brain tumors. Thus, combining multiple knowledge sources including knowledge from domain experts, historical documentary information and current records of actual instances, to develop a successful brain tumor diagnostic system is very important. From data supplied by Veterans' General Hospital (VGH) in Taipei, Taiwan, 12 parameters presently used in describing pictures derived by computerized axial tomography (CAT) scanning are shown in Table 1.

One of six possible classes of brain tumors including *pituitary adenoma, meningioma, medulloblastoma, glioblastoma, astrocytoma* and *anaplastic protoplasmic astrocytoma* (which are frequently found in Taiwan), must be identified. 348 actual cases of brain tumors from Veterans' General Hospital were used to evaluate the proposed system's performance. Table 2 shows an actual case expressed in terms of 12 features derived by computerized axial tomography (CAT) scanning, and a pathology report.

3. SYSTEM ARCHITECTURE

The brain tumor diagnostic system proposed here consists of three main units: knowledge building, knowledge inference and knowledge refinement. These three units respectively generate, use and alter the rules in the knowledge base (Fig. 3).

The knowledge building unit includes three modules: machine learning, knowledge acquisition and knowledge integration. The machine-learning module maintains a variety of learning methods (Michalski, 1980; Mitchell, 1982; Quinlan, 1986; Cendrowska, 1987) to induce various knowledge sources from different instance sets.

The knowledge-acquisition module maintains various knowledge acquisition tools (Kelly, 1955; Hwang & Tseng, 1990) that allow domain experts to input knowledge. Knowledge might then be directly obtained by various human experts using different knowledge-acquisition tools, or derived from different machine-learning methods. The knowledge-integration module rapidly combines multiple knowledge derived by the machine-learning module or the knowlege-acquisition module to build a prototype knowledge base. The knowledge-integration approach is an adaptive search method, thus eliminating a major difficulty in knowledge integration.

The knowledge inference component includes several modules: user interface, working memory, inference engine and explanation facility. The user interface helps users communicate easily with the expert system. The working memory stores facts that will be used during the course of a consultation. The inference engine generates new facts based on the rules and facts currently known. The explanation facility, when requested, explains the system's reasoning to the user.

A knowledge base integrated from multiple knowledge sources is often only a prototype, with

TABLE 1
Twelve Brain Tumor Attributes and their Possible Values

1. LOCATION:
   (1) Brain parenchyma
   a. frontal b. temporal c. parietal d. occipital e. thalamus f. basal ganglia g. corpus callosum
   (2) Interior surface of brain
   a. frontal horn b. body of lateral ventricle c. atrium d. occipital horn e. temporal horn f. third ventricle (anterior) g. posterior third ventricle h. pineal region
   (3) Brain surface (excluding skull base, vault)
   Convexity: a. frontal b. temporal c. parietal d. occipital
   Parasagital: e. frontal f. parietal g. occipital h. flax i. tentorium
   (4) Skull vault
   (5) Anterior skull base
   (6) Middle cranial fossa (excluding sella)
   a. clivus b. sphenoid ridge c. parasagital skull base
   (7) Sellar
   (8) Sellar and suprasellar
   (9) Suprasellar (including tuberculum sellar)
   (10) Parasellar
   (11) Cerebellopontine angle, ambiens cisterna
   (12) Brain stem
   (13) Fourth ventricle
   (14] Cerebellum (a. hemisphere b. vermis)
   (15) Cerebellar surface (extra-axial)
   (16) Cisterna magna (extra-axial)
2. PRECONTRAST:
   (1) Low (2) Iso (3) High (4) Mixed (5) With fat density (6) With air density
3. CALCIFICATION:
   (1) No (2) Marginal (3) Vascular-like (4) Lumpy, solid, punctate
4. EDENA:
   (1) No (2) <=2 cm (3) <=1/2 hemisphere (4) >1/2 hemisphere
5. SHAPE_EDEMA:
   (1) No (2) Smooth, regular (3) Digital, irregular
6. DEGREE_ENHANCEMENT:
   (1) No enhancement (2) Less than vessel (3) Same as vessel (4) More than vessel
7. APPEARANCE_ENHANCEMENT:
   (1) Homogeneous (2) Thin regular marginal (3) Moderate regular marginal (4) Thick regular marginal (5) Gyrus-like (6) Grossly irregular (7) Mural nodule (8) Homogeneous with lucency inside (9) Thick irregular marginal
8. GENERAL_APPEARANCE:
   (1) Grossly cystic with fluid inside but no mural nodule (2) Cystic with mural nodule (3) Solid with small cyst/cysts (4) Solid with necrosis (5) Solid without necrosis or cyst (6) Mass with hemorrhage (7) Infiltrative lesion (8) Gyrus-like involvement (9) Leptomeningeal lesion
9. BONE_CHANGE:
   (1) No bony change (2) Sellar enlargement (3) Internal auditory meatus enlargement (4) Bony sclerosis (5) Bony erosion (6) Bony destruction
10. SIZE (cm):
11. MASS_EFFECT:
   (1) No mass effect, infiltrative type (2) With mass effect (3) Ipsilateral enlargement of ambiens cisterna
12. HYDROCEPHALUS:
   (1) No hydrocephalus, no previous shunting (2) Yes (3) No, but shunted previously

TABLE 2
A Case for Brain Tumor Diagnosis

Feature	Feature value	Feature	Feature value
(1) Location	*sellar and suprasellar*	(7) Enhancement degree	*less than vessel*
(2) Precontrast	*high*	(8) Enhancement appearance	*homogeneous with lucency*
(3) Calcification	*marginal*	(9) General appearance	*solid with small cyst/cysts*
(4) Edema	*no*	(10) Bone change	*sellar enlargement*
(5) Shape edema	*smooth and regular*	(11) Mass effect	*with mass effect*
(6) Size	*1.2 cm*	(12) Hydrocephalus	*no hydrocephalus*
Pathology: *pituitary adenoma*			

unsatisfactory classification accuracy. Therefore, the prototype knowlege base must be refined. The knowledge-refinement unit automatically modifies the knowledge base according to results derived from the inference engine. The refinement algorithm also adopts an adaptive search method to alter the rules in the knowledge base.

In the following sections, we will concentrate on the knowledge-building unit and the knowledge-refinement unit since the knowledge-inference engine is similar to other widely used types.

4. KNOWLEDGE-BUILDING UNIT

Knowledge acquisition and machine learning are currently two major techniques for acquiring knowledge from experts and data respectively. These two techniques, however, have their own limitations as Gaines pointed out (Gaines, 1989). Knowledge derived from machine-learning methods is quite dependent on the training data used, which easily makes the induced knowledge incomplete. Knowledge acquired from experts is often biased toward the experts' opinions which can easily make the derived knowledge subjective. In order to effectively construct a complete, consistent and objective knowledge base for brain tumor diagnosis, we were concerned with acquiring knowlege by integration of the two techniques. Our aim was to construct an integrated brain-tumor diagnostic knowledge base from several individual knowledge sources.

The knowledge-building unit can help knowledge engineers effectively acquire and integrate knowledge from various types of sources. In the following subsection, we introduce the knowledge acquision, machine learning and knowlege integration functions.

4.1. Knowledge-Acquisition Module

Recently, much study has been devoted to eliciting different types of knowledge by interviewing experts. Various knowledge-acquisition tools have been successfully developed. In order to help BTDS easily acquire knowlege from various doctors, we included some commonly-used knowledge-acquisition tools in the

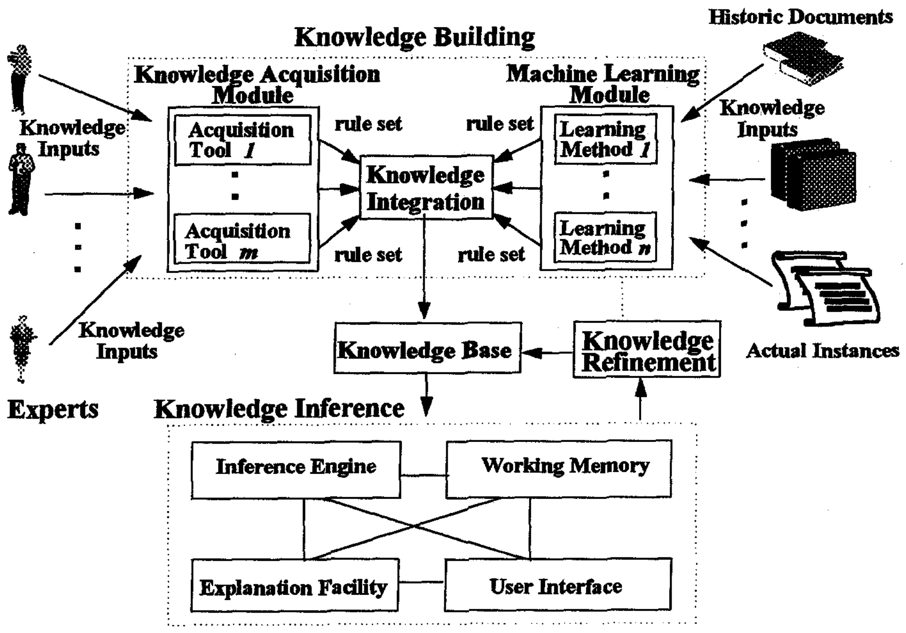


FIGURE 3. Structure of the brain tumor diagnostic system.

knowledge-acquisition module. The knowledge-acquisition module provides good flexibility and new knowledge-acquisition tools can be easily added to it. Experts can thus, depending on their preferences, choose the tools for knowledge input. The knowledge-acquisition module has a knowledge-acquisition-tool manager that provides a user-friendly interface for operating various knowledge-acquisition tools. The manager controls each knowledge-acquisition tool by invoking the services as required. Experts can thus easily apply any knowlege-acquisition tools to input their domain knowledge. Presently, two knowledge-acquisition tools, the Repertory Grid (Kelly, 1955) and EMCUD (Hwang & Tseng, 1990), are associated with the module. These tools meet the two general requirements described below.

(1) knowledge-acquisition tools must be domain-independent;
(2) the knowledge derived from tools must be easily translatable into the form of rules.

A brief description of these knowledge-acquisition tools is given as follows.

4.1.1. Knowledge-Acquisition Tool: Repertory Grid. Operation of the repertory grid (Kelly, 1955) by a single expert can be briefly described as follows:

Step 1. Elicit all the elements from the expert. At least two elements are needed to carry out the following procedure. Assume that five elements, E_1, E_2, E_3, E_4 and E_5, are provided by the expert; we place them across the top of a grid.

Step 2. Elicit constructs (traits and their opposites) from the expert. Each time three elements are chosen, ask for a construct to distinguish one element from the other two. The constructs obtained are listed down the side of the grid.

Step 3. Rate all of the entries (elements, constructs) in the grid. Assume the traits C_1, C_2, C_3, C_4 and their opposites C_1', C_2', C_3', C_4', have been given by the experts. As an example, the following repertory grid may be constructed.

	E_1	E_2	E_3	E_4	E_5	
C_1	5	1	5	1	1	C_1'
C_2	4	4	4	1	4	C_2'
C_3	1	4	5	1	4	C_3'
C_4	1	1	1	5	1	C_4'

Step 4. Generate production rules from the grids.

4.1.2. Knowledge-Acquisition Tool: EMCUD. EMCUD (Embedded Meanings Capturing and Uncertainty Deciding) (Hwang & Tseng, 1990) is a table-based knowledge acquisition method that can capture embedded meanings in given rules, and guide experts to decide certainty factors. The EMCUD strategy is briefly described as follows:

Step 1. Apply some repertory grid-oriented method to derive the initial knowledge.

Step 2. Construct an Attribute-Ordering Table that records the importance of each attribute to each object.

Step 3. Elicit embedded meanings from the original rules and Attribute-Ordering Table. Generate embedded rules for each original rule.

Step 4. Construct the constraint list to flag unwanted rules.

Step 5. Guide experts to decide certainty factors of the embedded rules.

4.2. Machine-Learning Module

Machine learning is another alternative for acquiring knowledge from training data. Recently, several expert systems have been created that use machine-learning methods to generate rules from data (Gray 1990). In order to help knowledge engineers easily acquire knowledge from various sources, we include some commonly-used machine-learning tools in the machine-learning module. Knowledge engineers can, depending on training data representation, choose suitable tools for knowledge induction. Each machine-learning tool has a data store to hold the derived knowledge. If the derived knowledge is not expressed in the form of rules, it is then translated into the form of rules. Presently, four machine-learning tools, including Version Space (Mitchell, 1982), ID3 (Quinlan, 1986), PRISM (Cendrowska, 1987) and AQR (Michalski, 1980), are associated with the module.

A brief description of these knowledge-acquisition tools is given as follows.

4.2.1. Machine-Learning Tool: Version Space. The Version Space learning strategy is mainly used for learning from training instances with only two classes: positive and negative (Mitchell, 1982). It attempts to induce concepts that include all positive training instances and exclude all negative training distances. The term "*version space*" is used to represent all legal hypotheses describable within a given concept-description language and consistent with all observed training instances. The term "*consistent*" means that each hypothesis includes all given positive training instances and excludes all given negative ones. A version space can then be represented by two sets of hypotheses: set $\boldsymbol{S}$ and dual set $\boldsymbol{G}$, defined as:

$S = \{s \mid s$ is a hypothesis consistent with observed instances. No other hypothesis exists that is both more specific than s and also consistent with all observed instances};

$G = \{g | g$ is a hypothesis consistent with observed instances. No other hypothesis exists which is both more general than g and also consistent with all observed instances}.

Sets S and G, together, precisely delimit a version space in which each hypothesis is both more general than some hypothesis in S and more specific than some hypothesis in G. When a new positive training instance is presented, set S is generalized to include this training instance; when a new negative training instance is presented, set G is specialized to exclude this training instance. When the Version Space is used to learn concepts from the multiple classes training set, one class is taken to be positive and all other classes are taken to be negative.

4.2.2. Machine-Learning Tool: ID3. In 1983, Quinlan proposed the ID3 learning algorithm that tries to form a decision tree from a set of training instances (Quinlan, 1986). ID3 uses the heuristics of minimizing "*entropy*" in determining which attribute should be selected next in the decision tree. If Attribute A has m values (i.e. $A_1, A_2, \ldots, A_m$) and the training set having attribute value A_i can be partitioned into n_i^+ positive training instances and n_i^- negative training instances, then the *entropy* of choosing A as the next attribute is calculated according to the following formula:

$$E = \sum_{i=0}^{m} -n_i^+ \log_2 \frac{n_i^+}{n_i^+ + n_i^-} - n_i^- \log_2 \frac{n_i^-}{n_i^+ + n_i^-}.$$

Among all the feasible attributes, the one that entails the least entropy will be chosen as the next attribute. The same procedure is repeated until each terminal node in the decision tree contains only training instances with the same class.

4.2.3. Machine-Learning Tool: PRISM. The PRISM learning algorithm maximizes *information gain* instead of minimizing *entropy* in inducing modular rules (Cendrowska, 1987). Attribute-valued pairs (*selectors*), in terms of *information theory*, can be thought of as discrete messages. Given a message i, the amount of information-gain about an event is defined as:

$$I(i) = \log_2 \left[\frac{\textit{probability of event after i is received}}{\textit{probability of event before i is received}} \right].$$

A *selector* (message) that provides more information-gain is then chosen to describe a class with a higher priority. The task of the PRISM learning algorithm is to find the selector α_x that contributes the most information-gain about a specified classificaton δ_n, that is, for which $I(\delta_n | \alpha_x)$ is maximum. The major difference between PRISM and ID3 is that PRISM concentrates on finding only relevant attribute-value pairs, while ID3 is concerned with finding only the attribute that is, the most relevant overall, even though some values of that attribute may be irrelevant.

4.2.4. Machine-Learning Tool: AQR. AQR is an induction algorithm for generating a set of classification rules (Michalski, 1980). When building decision rules, AQR performs a heuristic search through the hypothesis space to find the rules that account for all positive examples and no negative examples. AQR processes the training examples in stages; each stage generates a single rule, and then removes the examples it covers from the training set. This step is repeated until enough rules have been found to cover all the examples in the chosen class.

4.3. Knowledge-Integration Module

The knowledge-integration module exploits all the available knowledge in the knowledge-acquisition module and the machine-learning module to construct a system with good performance. Some benefits of integrating multiple knowledge sources in developing an expert system are described below (Medsker, 1995).

(1) Knowledge acquired from different sources has good validity;
(2) Domain knowledge is better understood from consensus among different knowledge sources;
(3) Integrated knowledge can deal with more complex problems;
(4) Knowledge integration may improve the performance of the knowledge base.

Since opinions of different domain experts are different, the knowledge derived from each expert will be different, too. A similar problem also arises when separate knowledge sets are generated by individual learning methods. These various knowledge sets must be merged into a comprehensive knowledge base for the system to perform well. However, incompleteness, redundancy and inconsistency often arise. Removing them in knowledge integration is thus very important in developing a good brain tumour diagnostic system.

The knowledge-integration module uses the *genetic algorithm* (Holland, 1975) as its integration engine to effectively integrate knowledge from multiple sources and rapidly construct a knowledge base. Here, we assume that all knowledge derived from the knowledge-acquisition and machine-learning modules are represented by rules since almost all knowledge derived by knowledge-acquisition tools or induced by machine-learning methods may easily be translated into or

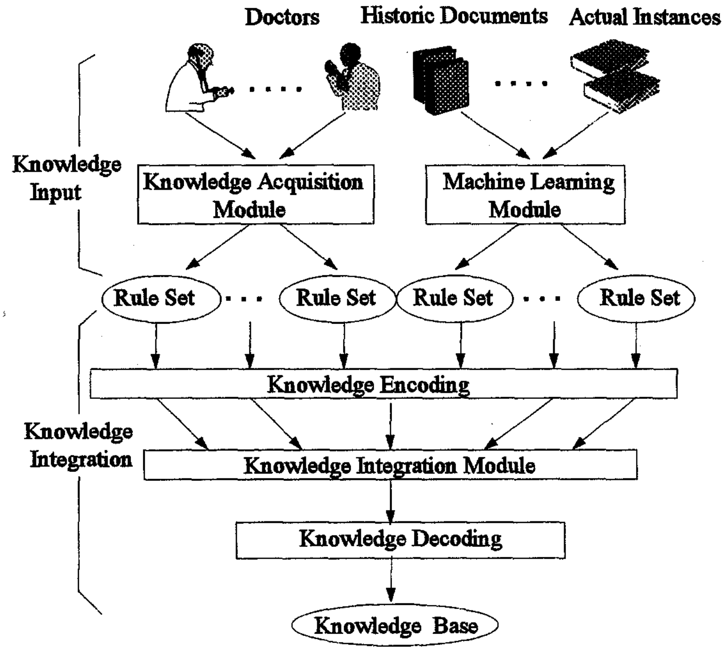


FIGURE 4. The flow chart of knowledge integration.

represented by rules.

The flow chart for knowledge input and knowledge integration is shown in Fig. 4. In the knowledge-input stage, knowledge is acquired from various experts or induced from different training sets, and is represented as rule sets. In the knowledge-integration stage, each rule set is encoded into a bit string. The knowledge-integration module maintains a population of possible rule sets (bit strings) and uses the *genetic algorithm* to automatically search for the best integrated rule set to use as the knowledge base (Liao, 1995).

The knowledge integration consists of three steps: *encoding*, *integration* and *decoding*. The encoding step transforms each rule set into a bit-string. The integration step chooses bit-string rule sets for "mating", gradually creating good offspring. The offspring then undergo recursive "evolution" until an optimal or a nearly optimal individual is found (Fig. 5). The decoding step then transforms the optimal or nearly optimal offspring into the form of rules.

Since rule sets generated from different knowledge sources may vary in size and rule-set sizes may not be known beforehand, using an appropriate data structure to encode rule sets is therefore very important. In our system, variable-length bit strings are used to represent rule sets (De Jong, 1988). An example is given below.

Example. Assume that two classes $\{C_1, C_2\}$ in rule set *RS* are to be distinguished using three features $\{F_1, F_2, F_3\}$. Assume Feature F_1 has three possible values $\{f_{11}, f_{12}, f_{13}\}$ Feature F_2 has four possible values $\{f_{21}, f_{22}, f_{23}, f_{24}\}$, and Feature F_3 had three possible values $\{f_{31}, f_{32}, f_{33}\}$. Also assume that the rule set *RS* has only two rules:

R_1: If $(F_1=f_{12})$ and $(F_2=f_{21})$ then *Class* is C_1;

R_2: If $(F_1=f_{11})$ and $(F_3=f_{32})$ then *Class* is C_2.

After encoding, the above rules are respectively repre-

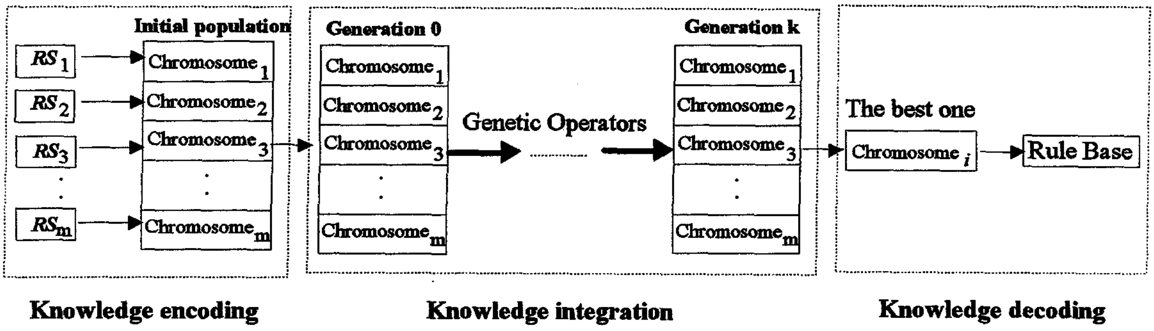
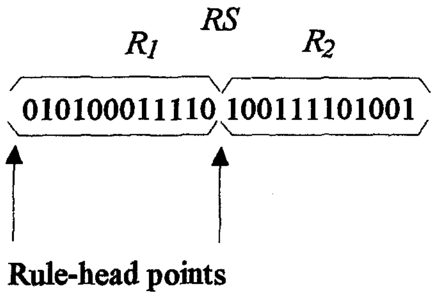


FIGURE 5. The knowledge-integration procedure.

sented as follows:

	F_1	F_2	F_3	*Class*
R_1	010	1000	111	10
R_2	100	1111	010	01

Finally, rule set *RS* is encoded into a chromosome:



Four genetic operators, *dynamic crossover*, *mutation*, *fusion* and *fission*, are applied to the rule-set population during knowlege integration (Liao, 1995). The *dynamic crossover* operator takes two parent chromosomes and swaps parts of their genetic information to produce offspring chromosomes. Unlike the conventional crossover operator, the dynamic crossover operator selects crossover points that need not be at the same point-positions on both parent chromosomes: instead, the crossover points are at the positions the same distance from rule-head points. The mutation operator randomly changes some elements in a selected rule set to help the integration process escape from local-optimum "traps". The *fusion* operator checks and eliminates rule redundancy and subsumption relationships using an "*OR*" operation. If a string resulting from an "*OR*" operation on two rules is the same as one of the two rules, then a redundancy or subsumption relationship exists between the two rules. The *fission* operator selects the "closest" *near-miss* (Winston, 1992) rule to eliminate misclassifications and contradictions.

In order to evaluate the fitness of an integrated rule set, an evaluation function is defined. The evaluation function considers two factors: accuracy and complexity. Here, "complexity" is evaluated by the ratio of rule-increase in the integrated rule set, and "accuracy" is evaluated by the degree to which the integrated rule set can correctly classify test instances. Accuracy and complexity are then combined to represent the fitness value of the rule set. The evaluation results are then fed back to the genetic algorithm to control how the solution space is searched to promote the quality of rule sets.

5. KNOWLEDGE-INFERENCE UNIT

Using the knowledge-integration approach proposed above, an integrated set of rules can be formed from multiple knowledge sources. These rules comprise a knowledge base for brain tumor diagnosis. Some rules in the knowledge base are described below:

rule 1: **IF** *Appearance_of_Enhancement* = *"Homogeneous"* and *Location* = *"Brain Parenchyma, temporal"* **THEN** *Pathology is Meningioma*

rule 2: **IF** *Appearance_of_Enhancement* = *"Moderate regular marginal"* and *Location* = *"Brain parenchyma, temporal"* **THEN** *Pathology is* ***Astrocytoma***

rule 3: **IF** *Edema* <= *"1/2 hemisphere"* and *Appearance_of_Enhancement* = *"Mural nodule"* and *Location* = *"Brain parenchyma, temporal"* **THEN** *Pathology is* ***Anaplastic Protoplasmic Astrocytoma***

rule 4: **IF** *Appearance_of_Enhancement* = *"Homogeneus with lucency inside"* and *Location* = *"Brain parenchyma, temporal"* **THEN** *Pathology is* ***Glioblastoma***

rule 5: **IF** *Appearance_of_Enhancement* = *"Moderate regular marginal"* and *Location* = *"Brain parenchyma, parietal"* **THEN** *Pathology is* ***Anaplastic Protoplasmic Astrocytoma***

rule 6: **IF** *Appearance_of_Enhancement* = *"Homogeneous with lucency inside"* and *Location* = *"Brain parenchyma, parietal"* **THEN** *Pathology is* ***Glioblastoma***

rule 7: **IF** *Precontrast* = *"Iso"* and *Location* = *"Brain parenchyma, occipital"* **THEN** *Pathology is* ***Meningioma***

rule 8: **IF** *Bone_Change* = *"Sellar enlargement"* and *Location* = *"Sellar and suprasellar"* **THEN** *Pathology is* ***Pituitary Adenoma***

rule 9: **IF** *Bone_Change* = *"Bony erosion"* and *Location* = *"Sellar and suprasellar"* **THEN** *Pathology is* ***Meningioma***

rule 10: **IF** *Precontrast* = *"Low"* and *Appearance_of_Enhancement* = *"Grossly irregular"* and *Location* = *"Cerebellum, vermis"* **THEN** *Pathology is* ***Astrocytoma***

rule 11: **IF** *Precontrast* = *"High"* and *Appearance_of_Enhancement* = *"Grossly irregular"* and *Location* = *"Cerebellum, vermis"* **THEN** *Pathology is* ***Medulloblastoma***

rule 12: **IF** *Appearance_of_Enhancement* = *"Homogeneous with lucency inside"* and *Location* = *"Cerebellum, vermis"* **THEN** *Pathology is* ***Medulloblastoma***

⋮

In the diagnostic process, BTDS can assist doctors in determining brain tumor etiologies according to the features extracted from computer tomography pictures. Doctors first inspect the patient's symptoms and input the symptoms as facts into the diagnostic system. The inference engine then searches for diagnostic rules that

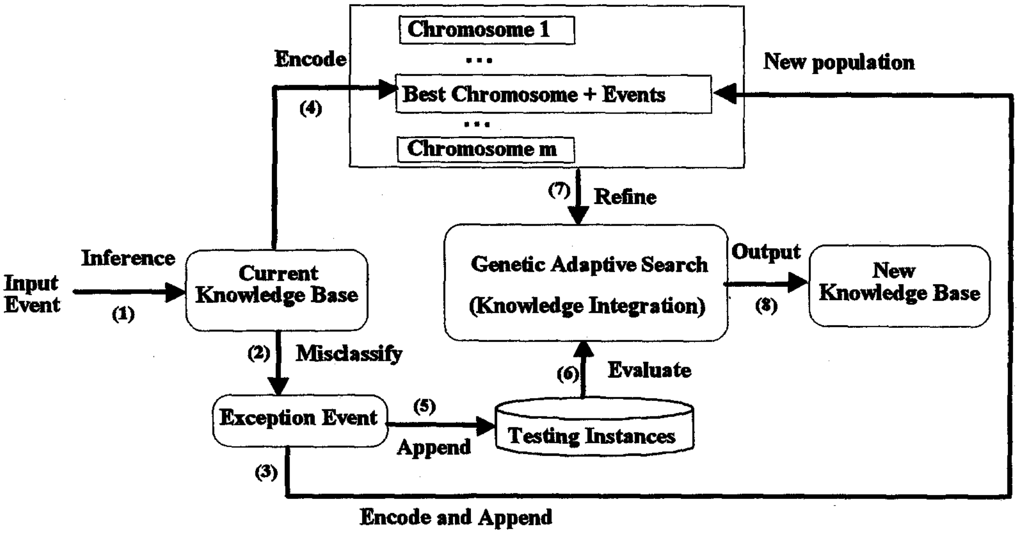


FIGURE 6. The knowledge refinement process.

match the patient's symptoms, and suggests a pathology.

6. KNOWLEDGE-REFINEMENT UNIT

A knowledge base integrated from multiple knowledge sources is often only a prototype, with an unsatisfactory classification accuracy. During the inference process, rules in a knowledge base must be refined to improve the effectiveness of the knowledge-base system. In this section, a knowledge-refinement scheme is proposed to refine rules during the inference process.

The knowledge-refinement unit uses the knowledge-integration procedure as the basis for refining knowledge. A flow chart for the refinement process is shown in Fig. 6. During inference, an input event wrongly classified by the current knowledge base is appended to the set of test instances. It is also encoded as a bit string and appended to the current best rule set. The new test set, including the wrongly-classified element, is then presented to the genetic adaptive search algorithm to evaluate rule sets for a new population. The refinement process works until the exception events can be correctly classified by the knowledge base, making the new knowledge base more accurate than the old one.

7. IMPLEMENTATION

The brain tumor diagnostic system was implemented in C language on a SUN SPARC/2 workstation. Ten initial knowledge items (rule sets) were obtained from different groups of experts using the knowledge-acquisition module, or derived from historical documents or current records of actual instances via machine-learning methods. The knowedge-integration module automatically integrated the ten initial rule sets into a comprehensive knowledge base. 348 real brain tumour cases were used to evaluate the performance of the knowledge base. After 2000 execution generations of the genetic algorithm, an accuracy rate of 91.42% was obtained, with 92 rules in the resulting knowledge base. The knowledge base must be continuously refined to improve the accuracy if misclassification occurs. These rules were then refined during the process of inference. Finally, an accuracy of 95.58% was achieved, with 103 rules in the resulting knowledge base.

8. CONCLUSIONS

This paper presents the design of a self-integrating knowledge-based brain tumor diagnostic system. The brain tumor diagnostic system proposed consists of three main units: knowledge building, knowledge inference, and knowledge refinement. Genetic techniques are also shown here to be good tools for knowledge integration and knowledge refinement. The system was successfully implemented on a Sun/SPARC 2 workstation. 348 real brain tumor cases were used to evaluate the performance of the brain tumor diagnostic system, with a classification accuracy higher than 95%. We may then conclude that the brain tumor diagnostic system is a successful medical system.

Acknowledgements—The authors would like to thank Dr M. M. H. Tseng and Dr O. Y Guo of VGH, for their advice about brain tumors.

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