Apply *FNN* Model to Construct Ontology-based Q&A System

Yau-Hwang Kuo
CREDIT Research Center
National Cheng Kung University
Tainan, 701, TAIWAN

Chang-Shing Lee
Department of Information Management
Chang Jung University
Tainan, 711, TAIWAN

Shu-Mei Guo
CREDIT Research Center
National Cheng Kung University
Tainan, 701, TAIWAN

Fu-Tsiang Tu
CREDIT Research Center
National Cheng Kung University
Tainan, 701, TAIWAN

Abstract—The Q&A (Question & Answer) knowledge base of an organization is important for knowledge management. It can provide experience and knowledge for a questioner. This paper applies a Fuzzy-Neural Network (*FNN*) model to construct Q&A knowledge base automatically. The *FNN* computes the important degree with sentences and infers the strength of each sentence for question properties. In addition, the back-propagation learning algorithm is adopted to train the question extractor. Moreover, we utilize natural language processing technology to analyze sentences of Chinese documents, and make use of Chinese knowledge bases to aid the selection of questions. The experimental results exhibit that the proposed approach can extract questions from Chinese documents effectively.

Key-Words: Ontology, Knowledge Base, Fuzzy Inference, Neural Network, Q&A, Knowledge Management.

1. INTRODUCTION

The ontology uses concepts and relations to classify domain knowledge. It conceptualizes a domain into a machine-readable format. Many applications of ontology have been proposed. For example, H. Alani et al. [1] propose an automatic ontology-based knowledge extraction from web documents. R. Navigli et al. [2] proposed an ontology learning and application to automated terminology translation. The authors used it to automatically translate multiword terms from English to Italian. R. N. Berthier et al. [3] propose an approach to extract information from unstructured documents based on an application ontology that describes a domain of interest. C. S. Lee et al. [4] proposed an ontology-based fuzzy event extraction agent for Chinese e-News summarization.

In recent years, knowledge management has referred to efforts to capture, store, and deploy knowledge. Question answering system is an important component of knowledge management. It can catch important knowledge and combine discussions to collect human experience. The first Q&A system was developed in the late 70s as interfaces to problem-solving system. The tradition of employing Q&A systems as interfaces to expert systems, using large knowledge bases and reasoning mechanisms continues even today. There are many Q&A systems have been proposed. For example, Burke et al. [5], S. Kim et al. [6], and J. Prager et al. [7] use the semantic knowledge base, WordNet, to improve the ability of matching questions and answers. Pasca et al. [8] propose the answer type taxonomy to extract answers. Litkowski [9] focus on essential keywords for questions and answers. S. Vassiliadis et al. [10] describe a question answering system based on fuzzy logic. The objective of this paper is to apply a FNN model to extract questions and answer from Chinese documents, and then construct a Q&A knowledge base automatically.

This paper is organized as follows. Section 2 describes the ontology-based for Q&A system. Section 3 introduces the knowledge extraction subsystem based on FNN model for Q&A system. The experimental results are shown in Section 4. Finally, Section 5 shows the conclusion.

2. ONTOLOGY-BASED Q&A SYSTEM

As currently practiced, the ontology is not only a knowledge base, but also defines the relationship of domain-specific knowledge. Fig. 1 shows the architecture of object-oriented ontology.

Corresponding Author: Prof. Chang-Shing Lee is with the Department of Information Management, Chang Jung University, Tainan, 711, Taiwan
Email: leecs@mail.cju.edu.tw, leecs@cad.csie.ncku.edu.tw

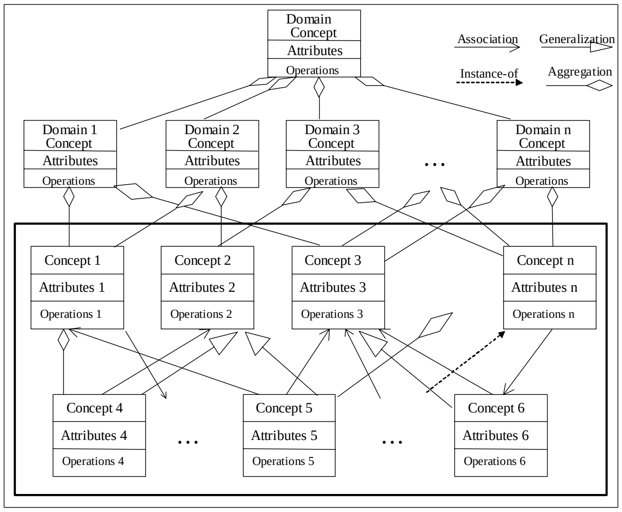

Fig. 1. The architecture of object-oriented ontology.

We use the object-oriented approach to represent the ontology architecture. The root is the domain concept and each domain concept contains sub-domain concepts or common concepts. Each concept may have three elements including concept name, attributes and operations, and have some relations to other concepts. In the object-oriented view, we treat a domain ontology as an object diagram and a concept as a class or an instance. The object diagram provides a formal graphic notation for modeling objects, classes, and their relationships to one another. In this architecture, there are two types of object diagrams, class diagrams and instance diagrams. A class diagram is a schema, pattern, or template for describing many possible instances of data. An instance diagram describes how a particular set of objects relates to each other. In our domain ontology, we combine class diagram with instance diagram; therefore, the "instance-of" becomes a relationship to present the relation between a class and an instance. One class describes one group of objects with similar properties, common behavior, common relationships to other objects, and common semantics. An attribute is a data value held by the objects in class. An operation is a function or transformation that may be applied to or by objects in a class. The attributes and operations in a concept are like them in a class. However, not each concept has attributes and operations; it may only have an association. An association describes a group of links with common structure and common semantics. It will represent the relationships between these concepts. In our Q&A system, there are three ontologies: domain ontology, question ontology, and answer ontology. The question ontology is one of domain ontology. It represents question domain knowledge. The answer ontology is the extension of domain ontology. It is based on domain ontology to develop the knowledge map of question. For the Q&A system, we add a specific attribute "Question type" into the concept of domain ontology. The attribute is important for the Q&A system to inference new questions and answers.

2.1 Question Ontology

Question ontology is one of domain ontology and defines all knowledge concepts from question domain. It contains the six kinds of question concepts including "what", "why", "who", "where", "when", and "how". Fig. 2 shows a part of question ontology.

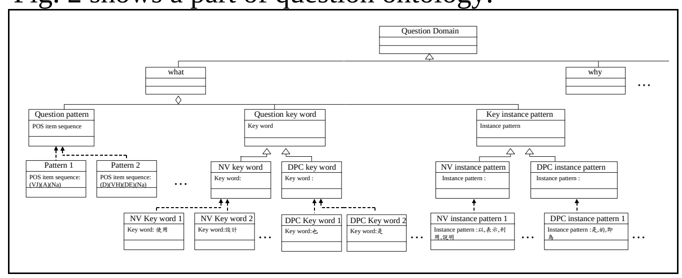

Fig. 2. A part of question ontology.

In Fig. 2, the question domain concept, such as "what" concept, contains three property concepts including question pattern concept, question keyword concept and key instance pattern concept. The question pattern concept consists of some POS patterns, extracted from many question sentences. The question keyword concept has two sub concepts including NV keyword concept and other keyword concepts. These keywords were selected by term frequency of question sentences. The key instance pattern concept contains NV instance pattern and other instance pattern, and these patterns are the frequent patterns of sentences.

2.2 Answer Ontology

The answer ontology is the knowledge map of Q&A knowledge base to help the answering process. Most importantly, answer ontology can speed up the answering process of question answering subsystem. It gives the knowledge map of Q&A database to support a quick search, then users can get the answer efficiently and correctly.

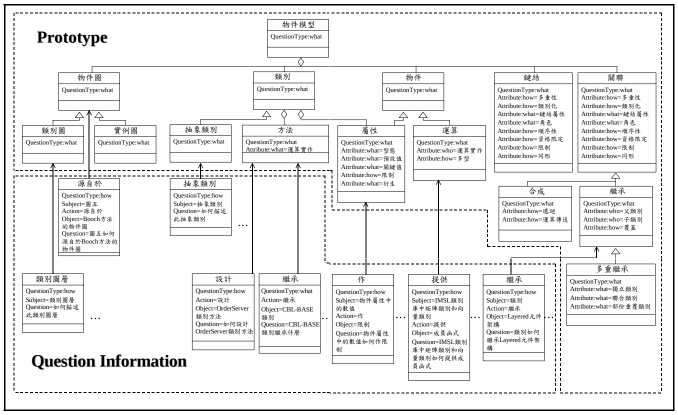

Fig. 3. A part of answer ontology.

Fig. 3 shows a part of answer ontology for Chinese documents. There are two partitions in the answer ontology. The “Prototype” partition is based on the structure of domain ontology and the “Question Information” is to record the information of questions in Q&A database. In Q&A knowledge base, we record the question and answer to Q&A database for one question, and abstract the key information of this question to answer ontology. In answer ontology, we use one question concept to present one question; the question concept presents the key information with five attributes. These attributes include (1) the question type of question QuestionType; (2) the subject of question Subject; (3) the behavior of question Action; (4) the objective of question Object; and (5) the file name of question Question. Based on the question type, we select the concept name of question concept.

2.3 Ontology-based Q&A system

In Q&A system, we discuss the automatic question generator and answer extraction mechanism. Our Q&A system contains three subsystems including knowledge extraction subsystem, Q&A knowledge base subsystem, and question answering subsystem. Fig. 4 shows the architecture of ontology-based Q&A system.

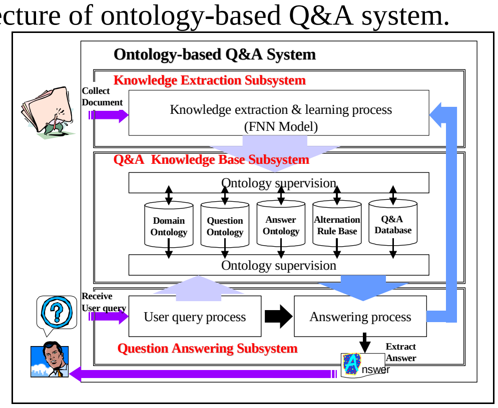

Fig. 4. The architecture of ontology-based Q&A system.

These subsystems supply the knowledge extraction capability and question answering services. In the knowledge extraction subsystem, we extract questions and answers from some documents to construct the knowledge base. Therefore, we use the Q&A ontology to represent the semantic knowledge of questions and answers, and use the Q&A database to record all questions and answers. Besides, we apply the constructed knowledge base to support question answering. When some users send their queries to Q&A system, the question answering subsystem transforms their queries to normal questions, and searches exist answers by the inference mechanism of knowledge base.

2.3.1 Q&A Knowledge Base Subsystem

The Q&A knowledge base subsystem has a knowledge base that contains history data and key knowledge, and an ontology supervision that can control all ontology and knowledge base. The knowledge base contains domain ontology, question ontology, answer ontology and alternation rule base, and this knowledge base supports the knowledge extraction subsystem to abstract questions and answers. The ontology supervision supplies the knowledge extraction subsystem and question answering subsystem with common APIs; these subsystems could use these common APIs to refer and modify this knowledge base.

2.3.2 Question Answering Subsystem

On question answering subsystem, we use Q&A knowledge base, domain ontology, question ontology, answer ontology and alternation rule base to search the correct answer. There are three mechanisms in question answering subsystem.

3. KNOWLEDGE EXTRACTION SUBSYSTEM BASED ON *FNN* MODEL

The knowledge extractor is the core technology of knowledge extraction subsystem. It applies the parallel fuzzy inference engine to extract the key sentences, and uses the FNN model to make question determination. The questions and answers extracted by knowledge extraction subsystem will be put into Q&A database. In addition, the answer ontology will be constructed by these questions and answers.

Fig. 5 shows the architecture of knowledge extraction subsystem. The inputs of this system are the Chinese documents and the outputs are modification information for Q&A knowledge base. In Fig. 5, the arrow from one component to the ontology supervision presents that the component refers to or modifies some knowledge bases by the ontology supervision.

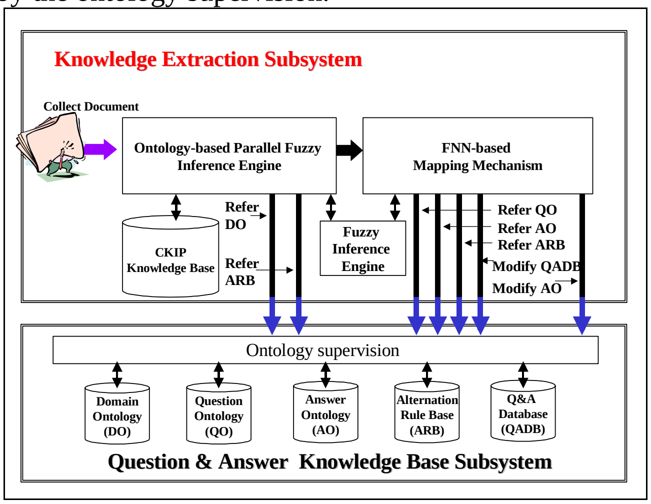

Fig. 5. The architecture of knowledge extraction subsystem.

3.1 Ontology-based Parallel Fuzzy Inference Engine

For various applications, there are many fuzzy inference models that have been proposed. For example, Kuo et al. [11] and Lin et al. [12] have presented the parallel fuzzy inference model and NN-based fuzzy model for different applications. In this paper, we embed and modify the former model to be a parallel fuzzy inference engine for sentence extraction. In question extraction process, the parallel fuzzy inference engine applies the domain ontology to select key sentences for a document. In general, there are three methods for key sentence selection. One is using the analysis with sentence semantic for natural language processing. One is using the machine learning methodology and history data. And, another is using the domain knowledge and inference mechanism. In this paper, we apply the inference model and domain knowledge to analyze document and select key sentences. Fig. 6 shows the parallel fuzzy inference engine architecture for ontology-based fuzzy inference. The parallel fuzzy inference engine contains seven layers, input linguistic layer, input term layer, rule layer, output term layer, output linguistic layer, output sentence layer, and output domain layer.

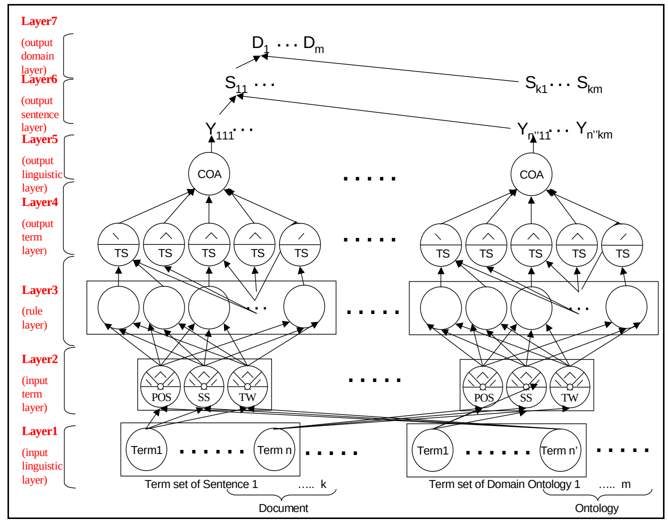

Fig. 6. The architecture of ontology-based parallel fuzzy inference engine.

In the input term layer, we propose three fuzzy variables for the similar strength of any two Chinese terms; they are strength in POS similarity, strength in semantic similarity, and strength in term weight. The first fuzzy variable of similar strength is strength in POS similarity (POS Similarity). First, we define the Chinese tagging tree by CKIP [14]. Fig. 7 shows a tagging tree structure that will be used to compute the strength of POS Similarity for any two Chinese terms [4]. The second fuzzy variable of similar strength is strength in semantic similarity (Semantic Similarity). In language view, a term may have many synonyms, but these synonyms are not perfect equal. In alternation rule base, the rule of term alternation can alternate a term with its synonym. The semantic similarity with two terms is depended on the times of alternation. For the third fuzzy variable of similar strength, strength in term weight (Term Weight), a term may exist in different domain ontologies, and plays the different role in each ontology. Hence, the strength in term weight is to define the weight for each ontology component.

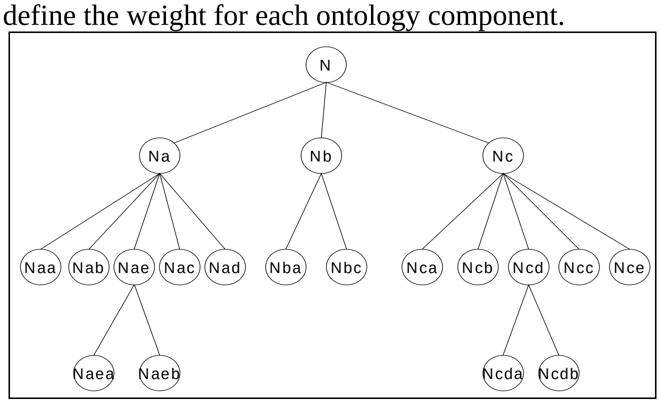

Fig. 7. The framework of Chinese tagging tree.

The rule layer that each node is a rule node to represent a fuzzy rule. The links in this layer are used to perform the precondition match of fuzzy logic rules. And, the output of a rule node in rule layer will be linked with associated linguistic nodes in the input term layer. Hence, each rule node of the rule layer should perform the fuzzy AND operation. In our model, we use the algebraic product operation to compute the matching degree. The output term layer performs the fuzzy OR operation to integrate the fired rules which have the same consequence. The fuzzy variable defined in output layer is Terms Strength (TS). The output linguistic layer performs the defuzzification process to get the TS of the Chinese term pair. In this paper, the center of area (COA) method [12] is adopted to carry out the defuzzified process. In output sentence layer, the engine gets all term strength for document term and domain ontology term. In output domain layer, the engine gets all sentence domain strength of sentences for each domain, and sums these strengths to determine the document category. Finally, we assume that Lk' is the length of k'th sentence. Hence, we could use the domain degree, sentence domain strength, and sentence length to calculate the key sentence strength KS of the k'th sentence. Eq. 1 shows the calculating equation.

$$KS_{k'} = \sum_{m'=1}^{m} \left(\frac{D_{m'}}{\sum_{h=1}^{m} D_h} \times S_{k'm'} \right) / L_{k'} \qquad (1)$$

Finally, the parallel fuzzy inference engine generates three outputs for one sentence, the key sentence strength, the question mapping degree, and the sentence domain for one sentence. Then we can select key sentences by key sentence strength, and determine questions by key sentence strength and question mapping degree.

3.2 FNN-based Mapping Mechanism

The FNN-based mapping mechanism in question extraction process decides what sentence is a question and translates the quasi-question to normal question. Then the mechanism extracts the answers of this question and stores them to Q&A database.

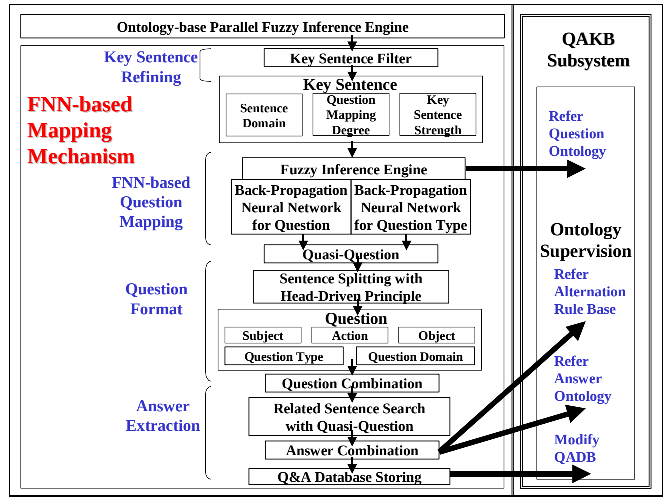

Fig. 8. The process of FNN-based mapping mechanism.

Fig. 8 shows the process of mapping mechanism. The FNN-based mapping mechanism consists of key sentence refining, question mapping, question format, and answer extraction. The key sentence filter refines out the noise sentences and retains the key sentences by setting the threshold for key sentence strength. In question mapping process, we construct a fuzzy inference engine and two back-propagation neural networks to determine what sentences are questions. The fuzzy inference engine compares key sentences and question ontology, and applies the fuzzy inference model to infer sentence question degrees for these sentences. There are two back-propagation neural networks in question mapping, one determined what sentence is a question, and another decided what is the question type for a question. These neural networks use the sentence information, question mapping degree, key sentence strength, and sentence question degree as the inputs to get the outputs. Then we analyze the network output, and generate the quasi-questions. In question format process, we split quasi-questions and use head-driven principle [13] to extract the head term of sentences. Hence the quasi-question could depend on the head term and question type to become a normal question. In answer extraction process, we search the related sentences with questions, and infer the size of answer window with these related sentences. Finally, we use these new questions to search exist question for answer ontology, and combine equal questions with them; then we save these questions to Q&A database.

In Fig.8, the question mapping is to extract questions from key sentences and decide the question type for them. Fig. 9 shows the architecture of FNN-based question mapping.

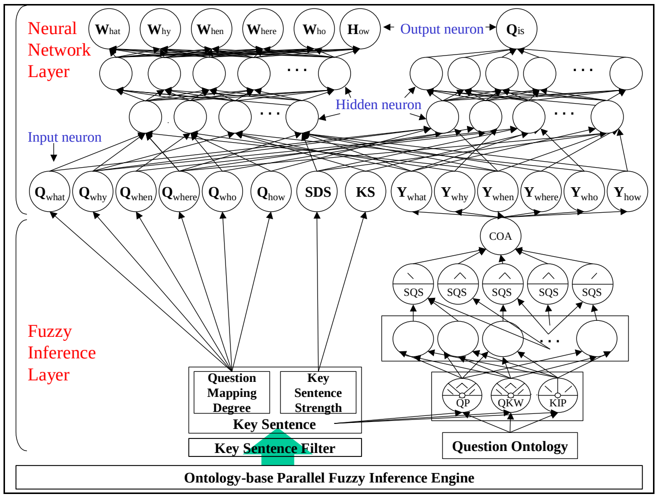

Fig. 9. The architecture of FNN-based question mapping.

In Fig. 9, the FNN-based question mapping has two layers including the fuzzy inference layer and neural network layer. The inputs of fuzzy inference layer are question ontology and key sentences supported by key sentence filter. The fuzzy inference layer outputs the sentence question strength for each key sentence. The neural network layer gets the output of fuzzy inference layer and the sentence information with key sentences to compute the network and output the quasi-question with one question type.

3.2.1 Fuzzy inference layer

The fuzzy inference model in this layer is similar to the model in parallel fuzzy inference engine; but in this layer, we just use the first five layers of the fuzzy inference model. In the input linguistic layer, the engine gets the key sentences with their POS and question ontology. In the input term layer, we consider three properties for key sentences, and infer the mapping strength with sentences and question ontology. The mapping strength means the degree of the mapping between one sentence and the ontology of one question type. Hence, the key sentence will have a higher possibility in one question type if they have stronger mapping strength. In this layer, we proposed three fuzzy variables for mapping strength of key sentence and question ontology; they are mapping strength in question pattern, mapping strength in question keyword, and mapping strength in key instance pattern.

The rule layer in fuzzy inference model is used to perform precondition matching of fuzzy logic rules. We use the algebraic product operation to compute the matching degree. The output term layer in fuzzy inference model performs the fuzzy OR operation to integrate the fired rules which have the same consequence. The fuzzy variable defined in output layer is Question Strength (QS). In the defuzzification process, we use the center of area (COA) method to get the sentence question degree of the key sentence. The sentence question degree presents the degree that this sentence belongs to one question type.

After the fuzzy inference model, we could get six sentence question degrees for six question types in one sentence, and use them to input the back-propagation neural network.

3.2.2 Neural network layer

The proposed fuzzy neural network uses fuzzy back-propagation learning [12]. We use two fuzzy neural networks to determine the degree of question and the question type. The numbers of input neurons in each network is fourteen. They are six question mapping degrees, two key sentence degrees and six sentence question degrees. The output for the first network with one output neuron is the degree of question. The second network with six output neurons decides the question type.

At last, for first network, we set a threshold β to evaluate the result of question determination. If the output value of the first network is higher than β, the sentence would be a quasi-question. For second network, we get the question type of this quasi-question by the network output, if the six outputs of the second network are not all 0 or 1, then we make the question type with the highest output value to the quasi-question. In the first network, we assign the output as 0 if the sentence isn't a question, and 1 if the sentence is a question. Then, the threshold should be greater than 0 but less than 1. Bascially, the value depends on the trained result of each sentence. After training the neural network, we will make the use of the fuzzy inference model to derive input features, and these networks for question determination.

4. Experimental Results

In this section, we use the Chinese documents of the object-oriented journal to be the experimental data. The object-oriented journal (http://www.misoo.com.tw) is a Chinese journal that presents object-oriented technique and introduces the practice of object-oriented technology. The journal has fourteen volumes during 1995~2001, and contains 154 articles with 17528 sentences. We use the first seven volumes with 9918 sentences to be the training data and last seven volumes to be the outside testing data. In each volume, the journal has a FAQ article, but in our research, these FAQ article will affect the impartiality of experiment; therefore, we filter noise articles, like the index file and FAQ articles, and translate journal articles to experimental data.

Now, we use the knowledge extraction subsystem to extract questions and answers as follows. Fig. 10 shows the demo interface for ontology-based Q&A system, and shows the results for question extraction process.

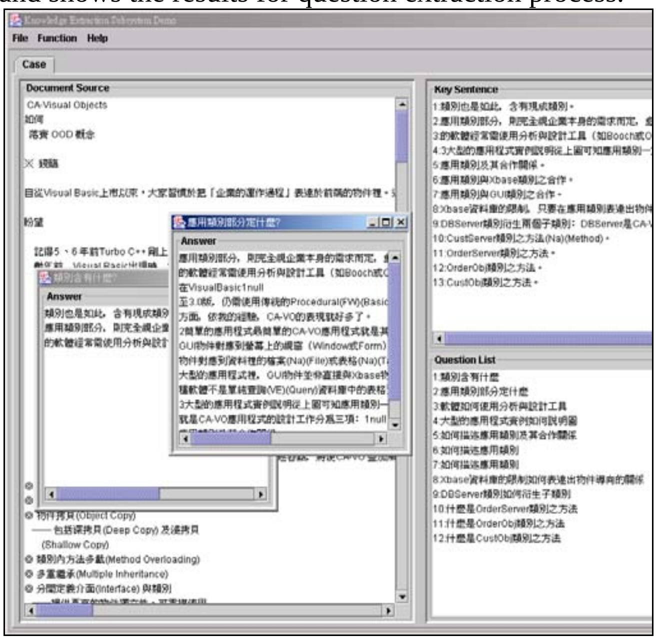

Fig. 10. The results of answer extraction.

5. CONCLUSIONS

In this paper, we have proposed a question and answer system with automatic question extraction capability. There are several novel techniques applied such as the fuzzy logic technology, neural network and natural language processing etc. The fuzzy logic technology is aimed at key sentence selection and question determination; meanwhile, the neural network supports the correct question determination and question type selection. Therefore, we can extract question based on our proposed ontology.

In addition, the proposed approach also integrates the knowledge extraction subsystem and Q&A knowledge base subsystem for question extraction, and combines these two subsystems with the question answering subsystem for question answering. In the future, we will develop a more efficient and effective answering algorithm for the Q&A system. Furthermore, the frequently-asked question (FAQ) system will also be studied.

ACKNOWLEDGEMENT

This work is partially supported by the National Science Council of Republic of China under grants NSC-92-2213-E-309-005.

REFERENCES

[1] H. Alani, S. Kim. D. Millard, M. Weal, W. Hall, P. Lewis, and N. Shadbot. "Automatic ontology-based knowledge extraction from web documents," *IEEE Intelligent System*, vol. 18, no. 1, pp. 14-21, Jan/Feb. 2003.

[2] R. Navigli, P. Velardi, and A. Gangemi. "Ontology learning and its application to automated terminology translation," *IEEE Intelligent System*, vol. 18, no. 1, pp. 22-31, Jan/Feb. 2003.

[3] R. N. Berthier, A. H. F. Laender, and A. S. da Silva, "Ontology-based extraction and structuring of information from data-rich unstructured documents," *Proc. 8th CIKM Conf.*, USA, Nov. 1999, pp. 52-59.

[4] C. S. Lee, Y. J. Chen, and Z. W. Jiang, "Ontology-based fuzzy event extraction agent for Chinese e-news summarization," *Expert System with Application*, vol. 25, no. 3, pp. 431-447, 2003.

[5] R. Burke, K. Hammond, V. Kulyukin, S. Lytinen, N. Tomuro, and S. Schoenberg, "Question Answering from Frequently-asked Question Files: Experiences with the FAQ Finder System," Technical Report TR-97-05, University of Chicage, Department of Computer Science, 1997.

[6] S. Kim, D. Baek, S. Kim, and H. Rim "Question Answering Considering Semantic Categories and Co-occurrence Density," *Proc. 9th Text Retrieval Conf.*, Maryland, Nov. 2000, pp. 317-325.

[7] J. Prager, J. Chu-Carrol, and K. Czuba, "Use of WordNet Hypernyms for Answering What-Is Questions," *Proc. 10th Text Retrieval Conf.*, Maryland, Nov. 2001, pp. 250-257.

[8] M. A. Pasca and S. M. Harabagiu, "High Performance Question/Answering," *Proc. 24th annual international ACM SIGIR conf. information retrieval*, Sep. 2001, pp. 336-374.

[9] K. C. Litkowski, "CL research experiments in TREC-10 question answering," *Proc. 10th Text Retrieval Conf.*, Maryland, Nov. 2001, pp. 122-131.

[10] S. Vassiliadis, G. Triantafyllos, and W. Kobrosly, "A fuzzy reasoning database question answering system," *IEEE Transactions on knowledge and data engineering*, vol. 6, no. 6, pp. 868-882, Dec. 1994.

[11] Y. H. Kuo, J. P. Hsu, and C. W. Wang, "A Parallel Fuzzy Inference Model with Distributed Prediction Scheme for Reinforcement Learning," *IEEE Trans. on Systems, Man, and Cybernetics*, vol. 28, no. 2, pp. 160-172, April, 1998.

[12] C. T. Lin, C. S. Gerorge Lee, "Neural-network-based fuzzy logic control and decision system," *IEEE Transactions on Computers*, vol. 40, no. 12, pp. 1320-1336, Dec. 1991.

[13] Head-Driven Principle, http://godel.iis.sinica.edu.tw/CKIP/treebank/

[14] Chinese Knowledge Information Processing Group, Academic sinica, Taiwan, 2003. http://godel.iis.sinica.edu.tw/CKIP/