A PILOT STUDY ON ENHANCING THE APPLICATION OF KNOWLEDGE MANAGEMENT SYSTEMS USING SEMANTIC SEGMENTATION

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Abstract

Owing to extensive knowledge management activities are promoted in various enterprises. How to enhance the application of knowledge management systems (KMS) becomes a critical issue. One of the enhanced applications of KMS is the SOS system, which aims at sharing knowledge for solving emerging problems. While it takes time for experienced employees to share their knowledge via the SOS system, it is advantageous to introduce an Automatic Problem Answering (APA) mechanism. When an emerging problem is issued, the APA mechanism will find actively suitable knowledge from the Intellectual Asset Repository (IAR), which consists of various sources of knowledge. In this paper, a semantic segmentation method is proposed and is employed in building a semantic segmentation module (SSM) in APA. SSM will automatically extract the knowledge corpuses embedded in documents. The extracted knowledge corpuses will be reused in APA to solve emergent problems and thus the application of KMS is enhanced.

KEYWORDS: Knowledge management, Text mining, Semantic segmentation

INTRODUCTION

More and more construction organizations have adopted commercial Knowledge Management Systems (KMS) for developing their own Knowledge Management (KM) functionalities. The existing KMS are mostly developed based on Communities of Practice (COP) for knowledge sharing and exchange (Yu, Yang, Tseng, & Yu, 2007). The SOS system is a specialized COP that provides real time aids for engineers/managers who are encountered with emergent problems. Once a problem is posed by a questioner in SOS, it will prompts automatically on the entry page of the KMS of every member. The SOS system has been proved to be very beneficial to the firm. Both tangible and intangible benefits were resulted significantly (Yu, Chang, & Liu, 2006).

The essential problem of existing COP in solving emergent problems is that the problem posed in the COP should “wait” the domain experts to provide solutions. Such “passive” mode of problem solving assumes that the domain experts can “see” the problem and respond with their solution timely. However, previous research found that such reactive problem solving (RPS) approach has caused inefficiency of timeliness and cost effectiveness of the KMS (Yu et al., 2007). To tackle with these problems, the Model of Proactive Problem Solving (MPPS) is proposed (Yu et al., 2007). Unlike RPS, the PPS proactively solves the problem through Automatic Problem Answering (APA) module. The Automatic Problem Answering module (APA) is an automatic problem solving system (APS) that searches the solution database called Intellectual Asset Repository (IAR) to provide the most appropriate answer to the problem.

One major limitation of the proposed PPS is the requirement of the historic lesson learned files (LLF). The LLF are compiled manually by the questioner who obtained solution from the domain experts. Compilation of previous experience of problem solving is expensive. Moreover, the project final reports, plans, proposals, and other knowledge documents contain tremendous engineering experiences that are valuable sources for solutions of solving problems. An automatic functionality should be developed to compile the explicit knowledge stored in those the abovementioned documents. In this pilot study, a semantic segmentation method from text mining is proposed and is employed in building a semantic segmentation module (SSM). Final reports are selected from a construction organization to serve as the research subject. The knowledge corpuses embedded in these reports were extracted by SSM automatically. The extracted knowledge corpuses will nourish IAR and be used in APA for solving future emergent problems.

The rest of the paper starts with reviews of related works to provide required backgrounds for SSM; the Model of Proactive Problem Solving (MPPS), which SSM is built on, is then briefly reviewed; then the implementation of SSM is presented to demonstrate the applicability of SSM; finally, conclusions and future works are drawn based on our research findings.

RELATED WORKS

Text mining, like data mining or knowledge discovery (Fayyad, Piatetsky-Shapiro, Smyth, & Uthurusamy, 1996), is often regarded as a process to find implicit, previously unknown, and potentially useful patterns from a large text repository (Tseng, Lin, & Lin, 2007). Semantic segmentation is one of the techniques in text mining. The aim of semantic segmentation is to segment a document into several thematic segments. Most of semantic segmentation researches (Beeferman, Berger, & Lafferty, 1999; Hearst, 1994) are based on the well known vector space model (VSM) (Salton & McGill, 1983; Salton, Wong, & Yang, 1975). Due to its popularity, the VSM based semantic segmentation techniques were employed in this study. VSM and related techniques of semantic segmentation will be described in the following subsections.

Vector Space Model

Vector Space Model (VSM) is the most popular model in information retrieval (IR) systems (Wu, Wei, & Tseng, 2007). In VSM, documents are represented as a Characteristic Vector (CV) which consists of n weights. Each weight represents the importance of a unique keyword in the document. The CV of document D_i can be represented with the Equation (1):

$$CV(D_i) = \{(k_1, w_{i1}), (k_2, w_{i2}), ..., (k_j, w_{ij}), ..., (k_n, w_{in})\} \tag{1}$$

where *CV(D_i)* is the characteristic vector of the *i*th document; K_j represents *j*th keyword; and W_{ij} is the weighting value of K_j in document D_i.

TF×IDF

A common approach used to determine the weight of a unique keyword is the well known TF×IDF (Term Frequency × Inverse Document Frequency) (Salton & McGill, 1983; Salton et al., 1975) method. It is a statistical measure for evaluating the importance of a term to the document it is contained. The importance increases proportionally to the frequency of the term (Term Frequency, TF) in the document, but is offset by the frequency of the term in the whole document collection (Inverse document frequency, IDF). TF×IDF is given as Equation (2):

$$W_{ij} = TF_{ij} \times IDF_j,\ IDF_j = \log\left(N / DF_j\right) \tag{2}$$

where TF_{ij} is the frequency of the *j*th term in the *i*th document (D_i); DF_j is the number of documents in which the *j*th term occurs at least once. The inverse document frequency (IDF_j) is calculated from the number of documents (N) divided by document frequency (DF_j).

IMportance Factor (IMF)

While TF×IDF is well known, the length of a term, which implies the importance of a term, is not considered. Based on TF×IDF, Wu et al. propose a novel modified TF×IDF scheme, called Importance Factor (IMF) (Wu et al., 2007). IMF is given as Equation (3):

$$IMF_{ij} = \frac{L_j}{L_{i,\max}}(0.5 + 0.5\frac{TF_{ij}}{TF_{i,\max}})IDF_j,\ IDF_j = \log\left(N / \sum_{i=1}^{N} C_{ij}\right) \tag{3}$$

where IMF_{ij} is the weighting of the *j*th term in the *i*th document (D_i); L_j is the length of the *j*th term; $L_{i,max}$ is the maximum length of terms in D_i; TF_{ij} is the number of occurrences for the *j*th term in D_i; $TF_{i,max}$ is the maximum number of occurrences for the terms in D_i; N is the number of LLFs in the repository; and C_{ij} = 1 if D_i contains term *j*, C_{ij} = 0, otherwise.

BRIEF REVIEW OF THE MODEL OF PROACTIVE PROBLEM SOLVING (MPPS)

The Model of Proactive Problem Solving (MPPS) is depicted in Figure 1. In the integrated framework, MPPS solves construction problems in two modes: (1) Automatic problem answering mode (APA mode)—the problem solving process is shown in Figure 1 as bold solid arrows, where the solution is searched automatically from historic lessons learned based on problem characteristics; (2) Automatic problem dispatching (APD) mode—the problem solving process is shown in Figure 1 as dashed arrows, where the unsolved problems (by APA mode) is automatically dispatched to the most related domain experts according to the problem characteristics and the Knowledge Capacity Matrix (KCM). The functions of problem solving in the traditional KMS is preserved and exercised in MPPS as shown in Figure 1 where the unsolved problem is posted in the COP of the KMS before entering the APD mode.

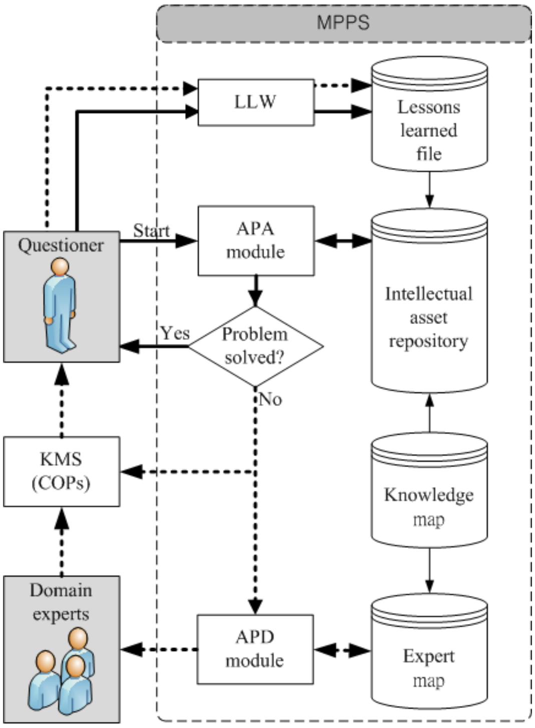


Figure 1: The Model of Proactive Problem Solving (MPPS)

Both the problems solved in APA and APD models are new lessons learned for future problems. This process is actually a verification of the knowledge to generate a higher level of intellectual asset called “wisdom”. This process is performed by Lessons Learned Wizard (LLW) as shown in Figure 1.

Versatility of the Intellectual Asset Repository (IAR) is the key to the success of APA. One major limitation of the MPPS is the nourishment of IAR depends only on historic LLFs. Since the manual compilation of previous experience of problem solving into LLF is costly and time consuming, IAR grows slowly. However, existing documents, such as proposals and final reports, of an organization are so versatile that knowledgeable works has been adequately kept in them. If the knowledge corpus can be extracted automatically from existing documents, IAR will be quickly nourished and the MPPS will become much more useful. In this study, a semantic segmentation method is proposed and is employed in building a semantic segmentation module (SSM) to tackle with this problem.

THE PROPOSED SEMANTIC SEGMENTATION METHOD

Project final reports, plans, proposals, and other knowledge documents are served as the intelligence collection of construction organizations. These knowledge documents contain tremendous engineering experiences that are valuable source for solving problems. Nevertheless, the employees are not always available to find the related documents when they are in trouble. Moreover, it would be too time consuming for employees to filter out the solutions they need, especially in long text documents which contain dozens of pages. To achieve fully automation of knowledge extractions for further enhancing the application of knowledge management systems, the semantic segmentation module (SSM) is developed.

Semantic Segmentation Module (SSM)

The enhancement of MPPS with SSM is shown in Figure 2. First, a knowledge document is loaded from the document repository. The characteristics of the text paragraphs included in the document are analyzed by SSM. Then, the similarities between each two consecutive text paragraphs are measured. The document is segmented into several semantic paragraphs by identifying the semantic segment boundaries according to a threshold of the similarity measurement. Then the semantic paragraphs extracted are saved in IAR. Once a question is posed by the questioner, the characteristics of the posed problem are analyzed by APA. Then, APA searches the IAR to find the most relevant solutions. Finally, the solution is retrieved and returned to questioner. As long as IAR is quickly nourished by the semantic segments (representing knowledge corpuses), it is more likely that the question can be solved.

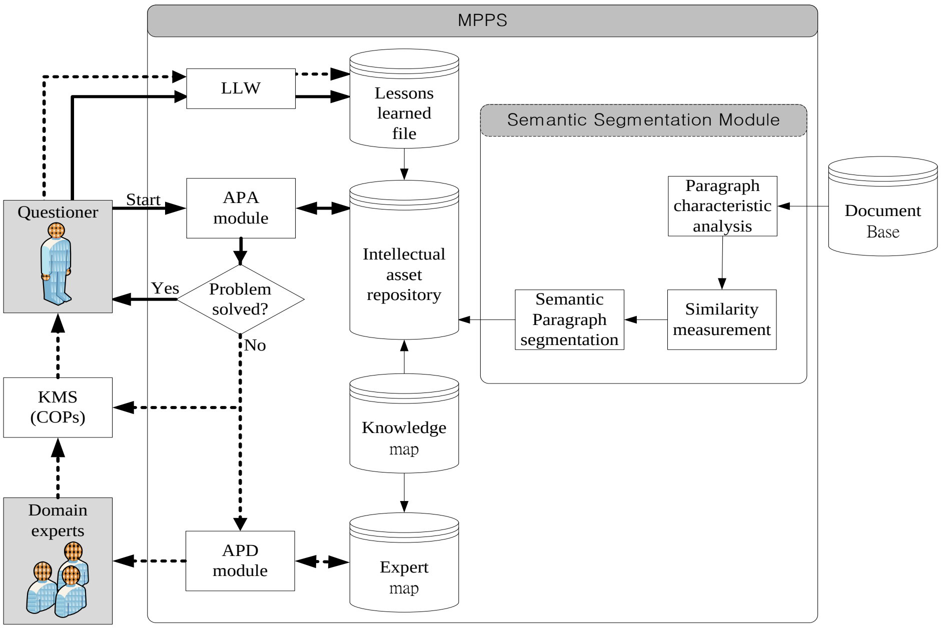


Figure 2: the enhancement of MPPS with SSM

The Process of SSM

The process of SSM is shown as Figure 3; it can be split into three main stages:

Text paragraph characteristic analysis

In this step, each of the text paragraphs contained in a document is transformed into a characteristic vector (CV) using VSM. At first, domain keywords contained in each paragraph are extracted. Second, the importance weightings of the keywords are calculated to form the CV of the paragraph using the Importance Factor (IMF) method as described in Section 2.3.

Similarity measurement

In this step, similarities between each two consecutive text paragraphs are measured using the inner product similarity measurement described in Equation (3):

$$S_{ik} = \sum_{j=1}^{n} \left(W_{ij} \times W_{kj} \right) \tag{3}$$

where S_{ik} is the similarity between text paragraph *i* and *k*; W_{ij} is the weighting of the *j*th element of the $CV(P_i)$; W_{kj} is the weighting of the *j*th element of the $CV(P_k)$. The pairs of text paragraphs with lower similarities are more likely to be segmented into different semantic paragraphs.

Semantic paragraph segmentation

The aim of semantic paragraph segmentation is to segment the document into several thematic segments, by determining boundaries between text paragraphs. In order to determine the boundaries, a threshold is empirically determined in advance. The pairs of text paragraphs will be segmented into different semantic paragraphs if the similarity measured is lower than the threshold. Finally, all the semantic paragraphs are extracted from the document and saved into IAR.

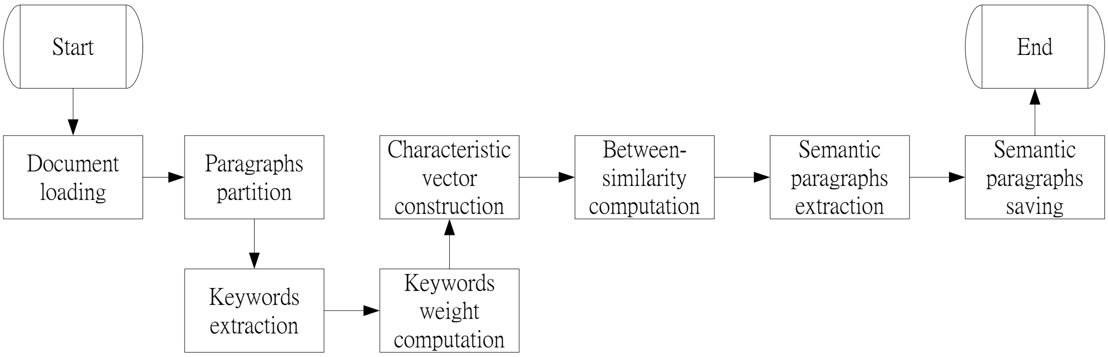
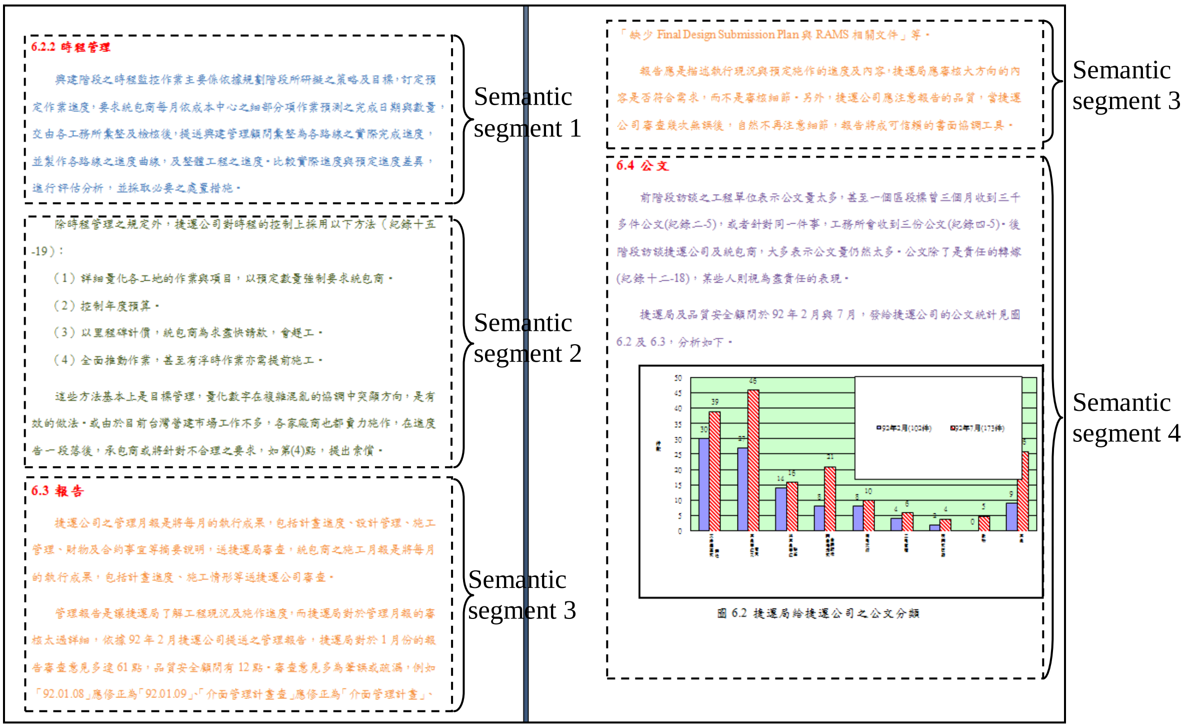

Start
End
Document loading
Paragraphs partition
Characteristic vector construction
Between-similarity computation
Semantic paragraphs extraction
Semantic paragraphs saving
Keywords extraction
Keywords weight computation

Figure 3: the process of SSM

SYSTEM IMPLEMENTATION

The proposed SSM has been implemented at current stage. Figure 4 shows an example of knowledge corpuses of a final report. In this example, the 2 –page text is segmented into four semantic paragraphs by SSM.



6.2.2 時程管理

興建階段之時程監控作業主要係依據規劃階段所研擬之策略及目標，訂定預定作業進度，要求統包商每月依成本中心之細部分項作業預測之完成日期與數量，交由各工務所彙整及檢核後，提送興建管理顧問彙整為各路線之實際完成進度，並製作各路線之進度曲線，及整體工程之進度。比較實際進度與預定進度差異，進行評估分析，並採取必要之處置措施。

Semantic segment 1

除時程管理之規定外，捷運公司對時程的控制上採用以下方法（紀錄十五-19）：

（1）詳細量化各工地的作業與項目，以預定數量強制要求統包商。

（2）控制年度預算。

（3）以里程碑計價，統包商為求盡快請款，會趕工。

（4）全面推動作業，甚至有浮時作業亦需提前施工。

這些方法基本上是目標管理，量化數字在複雜混亂的協調中突顯方向，是有效的做法。或由於目前台灣營建市場工作不多，各家廠商也都賣力施作，在進度告一段落後，承包商或將針對不合理之要求，如第(4)點，提出索償。

Semantic segment 2

6.3 報告

捷運公司之管理月報是將每月的執行成果，包括計畫進度、設計管理、施工管理、財物及合約事宜等摘要說明，送捷運局審查，統包商之施工月報是將每月的執行成果，包括計畫進度、施工情形等送捷運公司審查。

管理報告是讓捷運局了解工程現況及施作進度，而捷運局對於管理月報的審核太過詳細，依據 92 年 2 月捷運公司提送之管理報告，捷運局對於 1 月份的報告審查意見多達 61 點，品質安全顧問有 12 點。審查意見多為筆誤或疏漏，例如「92.01.08」應修正為「92.01.09」、「介面管理計畫查」應修正為「介面管理計畫」、

「缺少 Final Design Submission Plan 與 RAMS 相關文件」等。

報告應是描述執行現況與預定施作的進度及內容，捷運局應審核大方向的內容是否符合需求，而不是審核細節。另外，捷運公司應注意報告的品質，當捷運公司審查幾次無誤後，自然不再注意細節，報告將成可信賴的書面協調工具。

Semantic segment 3

Semantic segment 3

6.4 公文

前階段訪談之工程單位表示公文量太多，甚至一個區段標曾三個月收到三千多件公文(紀錄二-5)，或者針對同一件事，工務所會收到三份公文(紀錄四-5)。後階段訪談捷運公司及統包商，大多表示公文量仍然太多。公文除了是責任的轉嫁(紀錄十二-18)，某些人則視為盡責任的表現。

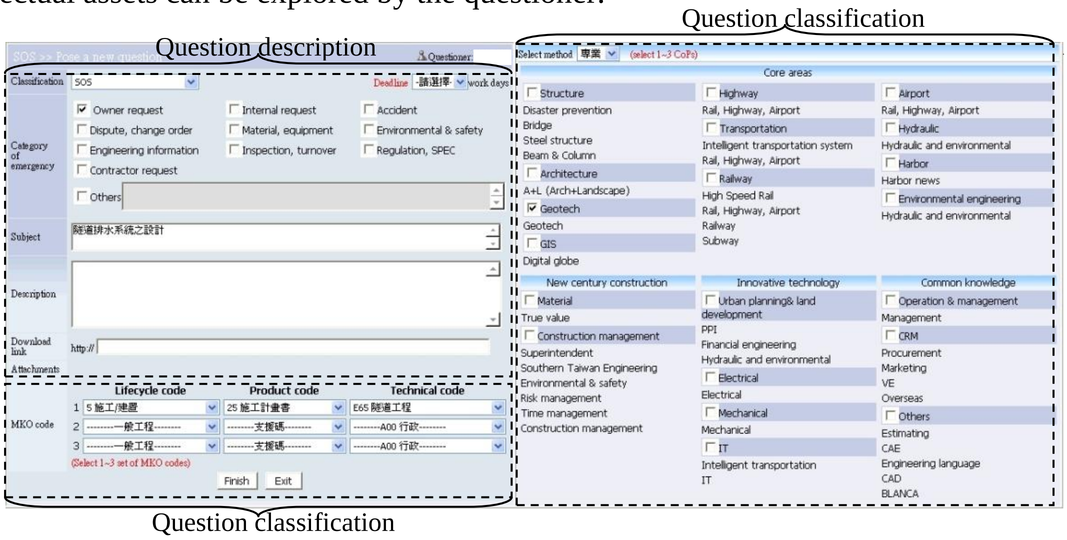
捷運局及品質安全顧問於 92 年 2 月與 7 月，發給捷運公司的公文統計見圖 6.2 及 6.3，分析如下。

圖 6.2 捷運局給捷運公司之公文分類

Semantic segment 4

Figure 4: An example of segmented knowledge corpuses

Figure 5 shows the interface of the APA module for posing the question. Once a question is posed by the questioner, APA searches the intelligential assets repository (IAR) to find the most relevant intellectual assets (either LLFs or semantic paragraphs). Then, the relevant intellectual assets can be explored by the questioner.



Question classification

Question description

SOS >> Pose a new question

Questioner:

Classification: SOS

Deadline: -請選擇- work days

Category of emergency:
☑ Owner request
☐ Internal request
☐ Accident
☐ Dispute, change order
☐ Material, equipment
☐ Environmental & safety
☐ Engineering information
☐ Inspection, turnover
☐ Regulation, SPEC
☐ Contractor request
☐ Others

Subject: 隧道排水系統之設計

Description:

Download link: http://

Attachments

MKO code:

	Lifecycle code	Product code	Technical code
1	5 施工/建置	25 施工計畫書	E65 隧道工程
2	--------一般工程--------	--------支援碼--------	--------A00 行政--------
3	--------一般工程--------	--------支援碼--------	--------A00 行政--------

(Select 1~3 set of MKO codes)

Select method: 專業 (select 1~3 CoPs)

Core areas

☐ Structure
Disaster prevention
Bridge
Steel structure
Beam & Column
☐ Architecture
A+L (Arch+Landscape)
☑ Geotech
Geotech
☐ GIS
Digital globe

☐ Highway
Rail, Highway, Airport
☐ Transportation
Intelligent transportation system
Rail, Highway, Airport
☐ Railway
High Speed Rail
Rail, Highway, Airport
Railway
Subway

☐ Airport
Rail, Highway, Airport
☐ Hydraulic
Hydraulic and environmental
☐ Harbor
Harbor news
☐ Environmental engineering
Hydraulic and environmental

New century construction

☐ Material
True value
☐ Construction management
Superintendent
Southern Taiwan Engineering
Environmental & safety
Risk management
Time management
Construction management

Innovative technology

☐ Urban planning& land development
PPI
Financial engineering
Hydraulic and environmental
☐ Electrical
Electrical
☐ Mechanical
Mechanical
☐ IT
Intelligent transportation
IT

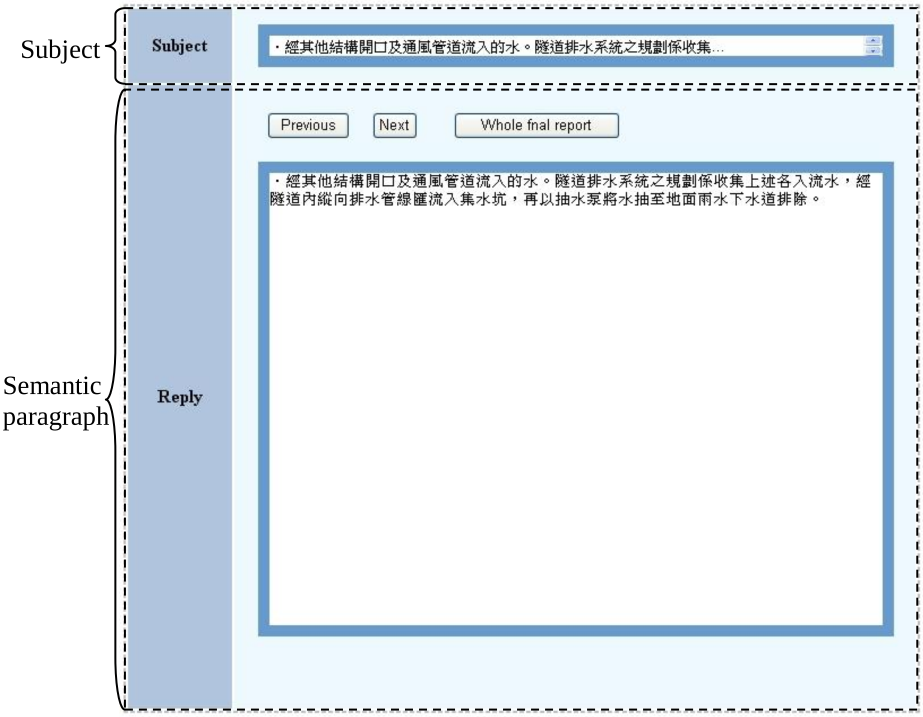
Common knowledge

☐ Operation & management
Management
☐ CRM
Procurement
Marketing
VE
Overseas
☐ Others
Estimating
CAE
Engineering language
CAD
BLANCA

Question classification

Figure 5: APA module—questioning

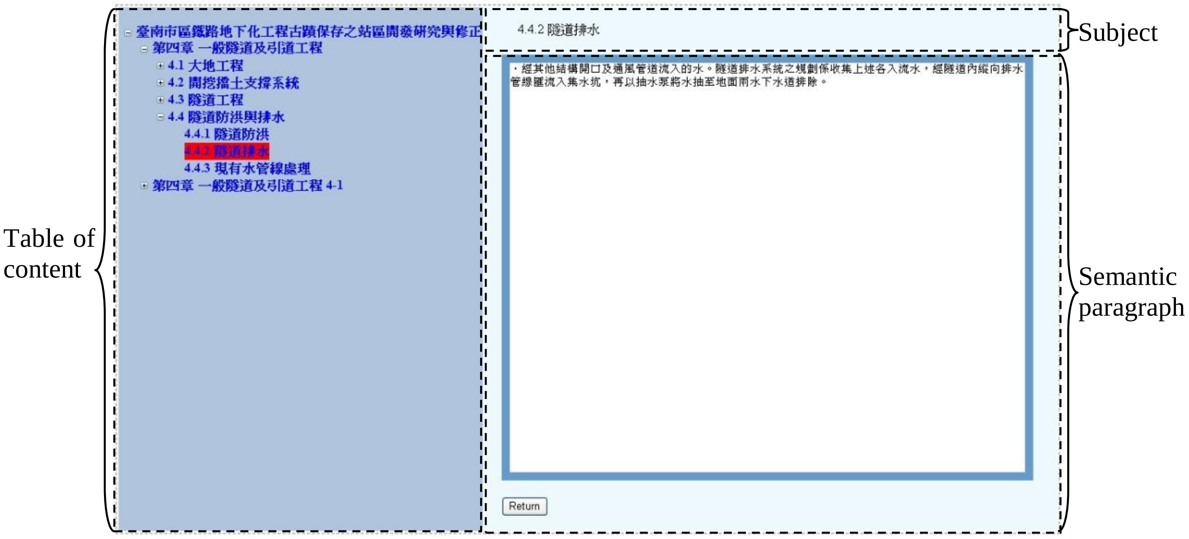
Figure 6 shows the interface of presenting a semantic paragraph to the questioner. The Questioner can not only read the relevant semantic paragraph but also explore the previous/next semantic segments or even the whole document. Figure 7 shows the interface that used for further exploring the whole document.



・經其他結構開口及通風管道流入的水。隧道排水系統之規劃係收集...

・經其他結構開口及通風管道流入的水。隧道排水系統之規劃係收集上述各入流水，經隧道內縱向排水管線匯流入集水坑，再以抽水泵將水抽至地面雨水下水道排除。

Figure 6: Example of a semantic paragraph



臺南市區鐵路地下化工程古蹟保存之站區開發研究與修正
第四章 一般隧道及引道工程
4.1 大地工程
4.2 開挖擋土支撐系統
4.3 隧道工程
4.4 隧道防洪與排水
4.4.1 隧道防洪
4.4.2 隧道排水
4.4.3 現有水管線處理
第四章 一般隧道及引道工程 4-1

4.4.2 隧道排水

・經其他結構開口及通風管道流入的水。隧道排水系統之規劃係收集上述各入流水，經隧道內縱向排水管線匯流入集水坑，再以抽水泵將水抽至地面雨水下水道排除。

Figure 7: Example of presenting the whole final report

CONCLUSIONS

A semantic segmentation module (SSM) is proposed and developed in this paper. SSM automatically extract the knowledge corpuses embedded in reports and documents which are collected over years in an enterprise. The SSM not only improve the previously developed PPS system, but also begin to intellectualize the existing knowledge assets. The extracted knowledge corpuses will be reused in APA to solve emergent problems and thus the application of KMS is enhanced.

Even though preliminary results show promising benefits of the proposed SSM, future verification are required to validate the implementation of SSM, including: (1) quantitative evaluation of time and cost effectiveness; (2) verification of correctness of semantic segments extracted by SSM. Moreover, the proposed SSM can only extract text type knowledge assets. In the future, figure extraction, table extraction and semantic relation construction techniques will be added to MPPS to deal with more kinds of knowledge assets.

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