Applying Mobile Learning and Word Sense Disambiguation in E-book for English-Learning Assistance

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Abstract

E-book has become a popular trend and thus how to develop an attractive e-book system is an important issue. In the global environment, enhancing foreign language skill is critical. E-books allow a reader to learn English anywhere at any time. It is beneficial and practical for learners. This study presents an English-learning assistance e-book (LAE) which includes two major components, namely, learning notes and translation of vocabulary. First, learning notes record personal study notes which can be reviewed anywhere anytime. Second, for determining the best translation of an English word with respect to its context, our approach integrates three pieces of information including similarity degree, co-occurrence in Web, and the most frequent sense. Experiment results show that the proposed approach outperformed existing methods. Therefore, LAE is able to help enhance the efficiency of learning via an E-book.

Keywords: English-Learning Assistance, Word Sense Disambiguation, Mobile Learning, E-book.

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I. INTRODUCTION

Digital products are essential to daily life, and many traditional products have become digitalized, such as e-books. Most of e-books just digitized the books so that e-books have the same function and content as the paper-form books. Such e-books do not help improve reading easiness for the readers. As a result, readers do not particularly prefer e-books (Shepperd et al. 2008). In a recent experiment of student buying patterns, 90% of the students prefer to buy textbooks, which are more expensive, but they did not want to buy the e-books. Therefore, e-books need to have unique and useful features in order to attract readers.

In a global environment, enhancing foreign language skill is important. An environment which allows a reader to learning English anywhere anytime is beneficial and practical. Therefore, the development of e-books facilitating English learning is critical. In addition, the regular learning-based e-books have two shortcomings:

1. The e-books do not allow making notes during reading. Learners cannot record comments during learning, which leads to difficulty in review.
2. The e-books do not support recommendation of appropriate vocabulary translation in the article. A limited vocabulary often leads to misunderstanding or poor comprehension of English texts (Chu et al. 2002). Therefore, it is important to provide appropriate translation in the article.

In this study, we aim to present an English-learning Assistance e-book (LAE) based on word sense disambiguation (WSD) and personal learning notes. Over the past few years a considerable number of studies have been made on WSD. Therefore, we integrate the previous method (Wu 2011) and LAE to produce an improved method. The system consists of four parts. First, the previous study (Wu 2011) has exploited context and vocabulary translation to calculate the similarity with WordNet hyponyms. Second, the authors in (Agirre et al. 2009; Fernandez-Amoros et al. 2011) have confirmed that the first of the word's senses in the dictionary has a high accuracy for vocabulary translation; therefore, we use the finding to enhance the accuracy of vocabulary translation. Third, we find vocabulary and the article topics relevant in the Web. Finally, we give the three factors different weights and then calculate the final score.

Study notes are important for learners. However, only a few e-books provide this functionality. Therefore, we provide learning notes which learners can record personal study notes for review anywhere at any time.

This paper includes into six sections. In section 2, we review previous work including mobile learning, WSD and WordNet. In section 3, we propose an English-learning Assistance e-book based on WSD and personal learning notes. In section 4, we present experimental result of translation of vocabulary. Finally, future work and contributions are described.

II. LITERATURE REVIEW

In this section, we briefly review the related studies, introducing mobile learning, word sense disambiguation, and WordNet.

2.1 Mobile Learning

Mobile learning is new trend in learning model, which mobile device access teaching information anywhere anytime. For mobile system not only contain educational but also support adequate visualization on mobile device (Georgieva et al. 2011).

In the past, researchers used sensing technologies to provide more effective learning. For example, the author (Gass 1988) developed a mobile learning system in order to train students to identify the features of plants on a school campus. Researchers have pointed out situated learning environments that would afford particular knowledge to be learned (Chen et al. 2003). Different from traditional mode, mobile learning seems to be a more attractive learning way that can interest learners. on the other hand, the research conducted, mobile learning has not reached stable state (Luvai F 2007) .

We should conclude that mobile learning focuses on learning anywhere anytime. Today's teaching or learning mode usually teaches in a close place. However, mobile learning reduces limitation of learning and improves convenience for the learner. Therefore, we consider using mobile learning theory to construct our English-learning Assistance e-book.

2.2 Word sense disambiguation

There exist many techniques that are used for word sense disambiguation (Yoon et al. 2007). The WSD mode divided into manual and automatic. Which one is chosen depends on the final goal, if the final goal needs to use on learners of large number, it must chose the automation. For example, through the context of articles automatically exclude ambiguity, to determine the most appropriate vocabulary translation of the article (Wu 2011).

Manual mode obtain higher precision than automatic, however, the approach that need to use artificial rule (Small 1980; Wilks 1972) which cost is too high. And automatic mode can use a huge dictionary or corpora in internet. But, the accuracy is lower than Manual mode. Therefore, to select WSD mode between manual and automatic is important issues.

It has been common to use two kinds of resources: a dictionary and corpora. (Lesk 1986) The first resource, a dictionary defined the related words as frequently co-occurring words in context (Wilks et al. 1990).

The second resource for WSD is corpora. Corpus-based methods have two types: supervised learning and unsupervised learning. Supervised learning often used for WSD. These techniques provided outcome so that it can take corrective action during in learning or training phase. Another type is unsupervised learning trying to match pre-specified categories from input parameters (Leroy et al. 2005).

Much existing research used WSD method to grasp the sense for words (Hwang et al. 2011), which include a paragraph or a sentence. While have two types for this research (Tacoa et al. 2010):

1. Graph-based method: A graph constructed, which nodes represent word meanings and edges relations between two nodes. Next, after applying a semantic similarity measure. Previous works in (Sinha et al. 2007) proposes an unsupervised graph-based method for disambiguation.
2. Semantic role labeling for WSD: It performs disambiguation of sense. Next, disambiguation of arguments. Finally, disambiguation of semantic roles. Previous works in (Moreda et al. 2006; Pozo et al. 2004).

2.3 WordNet

The WordNet is a large lexical database of the English language, which is developed by Cognitive Science Laboratory at Princeton University under the guidance of Professor George A. Miller. Terms in WordNet are grouped into sets of cognitive synonyms, called synsets which are interlinked by conceptual-semantic and lexical relations such as hyponym, hypernym, synonym, antonym, cause, coordinate term, entailment, holonym, meronym, and attribute (Huang et al. 2009). WordNet 3.0 contains 155,287 strings with 117,659 synsets. Table 1 shows the distribution of words across the parts of speech.

Table 1 Word distribution in WordNet 3.0

Part of speech	# Unique Strings	# Synsets
Noun	117,798	82,115
Verb	11,529	13,767
Adjective	21,479	18,156
Adverb	4,481	3,621
Total:	155,287	117,659

III. METHOD

In this section, we first describe system architecture and then the detail of its two subsystems: personal learning notes and word sense disambiguation.

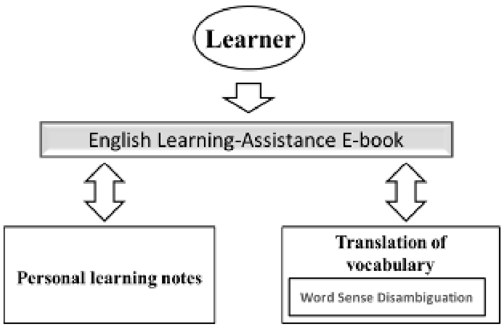
3.1 System architecture

The English-learning Assistance e-book (LAE) consists of personal learning notes and translation of vocabulary. Figure 1 shows the details of system architecture. The learning notes record personal study notes which can be reviewed anywhere at the later time. The translation of vocabulary mechanism is based on the WSD technique.

3.2 Components of System

In this section, we describe the components of the system. The system components of

LAE are shown in Figure. 2.



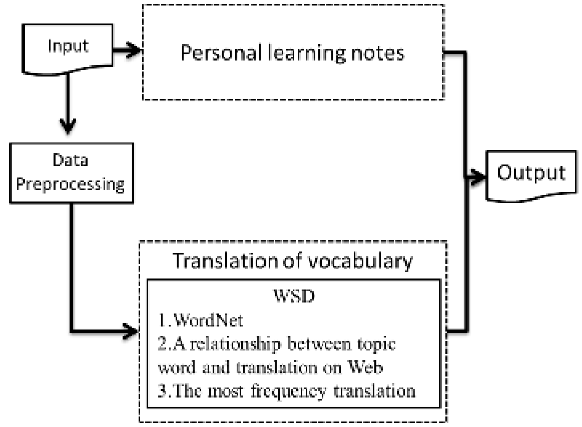


Figure 1. System architecture of LAE

Figure 2. System components of LAE

3.3 Personal learning notes

This function allows the user to highlight notes in the article. We need to capture the selected location and highlight attribute. Therefore, to save the highlights, the system records four parameters, the start position, the end position, font color and the button line, respectively. When the user opens the article next time, the system reads the saved parameters and set the text according to the configuration. A note on an e-book is shown in Figure 3.

Figure 3. Making Notes on e-books (a) Select the text of note (b) Select the type of annotation (c) The result of annotation

3.4 Data Preprocessing

Data preprocessing is the first step of the WSD because articles have unstructured formats containing stop words, numbers and tags which contain only a small amount of information about the article. The unstructured format may lead to reduced performance. Therefore, we use data preprocessing to exclude the lowly related terms in the articles. The processing steps are shown in Figure 4 (Wu 2011).

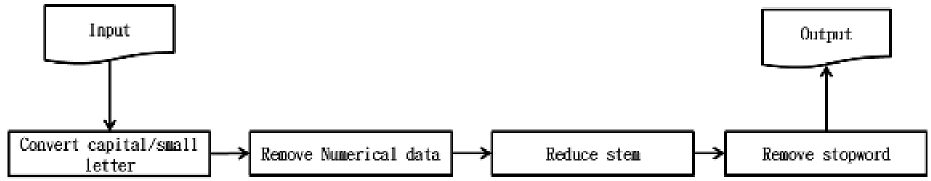


Figure 4. The steps of data preprocessing

The steps of data preprocessing are described in details as below:

1. Convert capital/small letter:

All the vocabulary is converted into lower case, because we consider them the same word regardless the upper or lower case.

2. Remove numerical data:

Numeric data, such as date, time, and year, are irrelevant to vocabulary learning. Therefore, they can be removed.

3. Stem words:

This step would convert the different verb tenses into the present tense. For example, “break”, “broke” and “broken” are conflated into a single stem.

4. Remove stopwords:

Stopwords appear frequently in an article, such as ”I”, “he”, ”she”, “am”, “are”, “is”, but they are unimportant in an article with respect to vocabulary learning. Therefore, they can be removed.

3.4.1 Translation of vocabulary

Many studies showed it is helpful to a learner by providing the most appropriate translation (or sense) of a word in the article. We consider the use of three pieces of information to achieve this function which identifies the most appropriate translation. The process of determining the best sense consists of four steps, as shown in Figure 5.

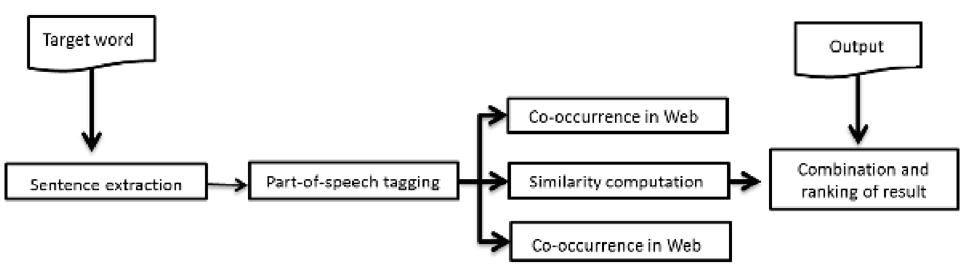


Figure 5. The steps of word sense disambiguation

The steps of WSD are described in details as below:

1. Sentence extraction

In this step, we extract the original sentence containing the target word. The sentence extraction is a preprocessing for translation of vocabulary. The extracted sentence can also be used in part-of-speech tagging and similarity calculation (Wu 2011). The algorithm of sentence extraction is shown in algorithm 1.

In algorithm 1, the inputs are the target word *w* and source document *d*. the output context sentence *C* containing the target word. *p* is position of target word. getWord(*p*) is the word of index *p*. The result is the original context sentence containing the target word.

Algorithm 1: The algorithm of GetContext

```
Input: the target word w, the source document d
Output: the context sentence containing target word C
1.   Set parameter: position of target word p, position of previous sentence preFlag, position of end sentence endFlag
2.   Find the start and end points
2.1  To find a starting point
     do
        If getword(p) is this sentence dot,
           If getword(p) is last sentence dot,
             preFlag = p+1
              break
           Else
              p = p -1
        Else
              p = p-1
     while (to find a starting point)
2.2 To find an end point
    do
        If getword(p) is this sentence dot,
         If getword(p) is next sentence dot,
             endFlag = p-1
          break
          Else
             p = p +1
        Else
         p = p+1
     while (to find an end point);
        C is return getWords(lastFlag, endFlag)
```

2. Part of Speech tagging

In this step, we determine and mark part of speech of each word in the original sentence. In fact, a word may have multiple parts of speech in WordNet, and in each part of speech the word may have different senses. Therefore, if we can determine the part of speech of the target word in the sentence, this result can not only reduce the number of candidate senses to be determined in the next phase but also enhance the accuracy of WSD. We use LingPipe (http://alias-i.com/lingpipe) to perform tagging. LingPipe is a tool kit for processing text using computational linguistics, and this tool is a java-based utility (Wu 2011).

A word may have multiple Part-of-Speeches, such as noun, verb, adjective, adverb, etc. We get the part of speech of the target word in the article. If the marking result of a world is verb, we just only need to focus on the senses of the verb. An example of part-of-speech marking is shown in Figure 6.

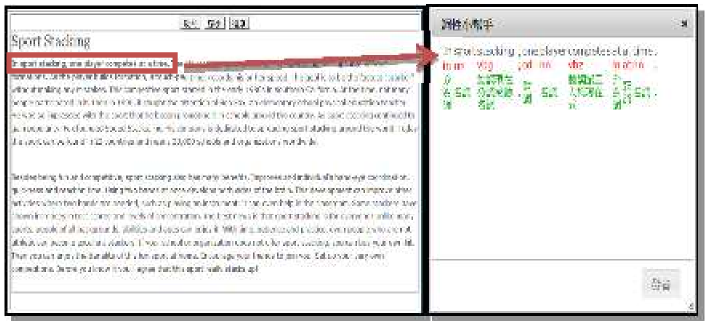


Figure 6. Determine parts of speech of words in a sentence

3. Co-occurrence in Web

This step is to measure correlation degree between the sense of the target word and the article. We obtain co-occurrence frequency between the sense of the target word and the title of the article by Google search engine. We capture the title of the article and vocabulary translation which are inputted to the Google search engine. The result means the degree of correlation between the title of the article and translation of the target word. Therefore, candidate translation which has the highest frequency is identified as the most appropriate translation.

For example, the target word is “Energy” which has a sense of xxx and the article title is “Healthy again”. We input “元氣 體力 活力 Healthy again” to Google engine, and get frequency. The detail is shown in Table 2

Table 2. Co-occurrence in Web of sense and article title

Translation of “Energy”	Input: title and translation of target word	Output: frequency of Google search
元氣 體力 活力	Healthy again 元氣 體力 活力	5,720
能源 能量	Healthy again 能源 能量	153,000
精力 精神 活力	Healthy again 精力 精神 活力	171,000
體力 力氣	Healthy again 體力 力氣	190,000

Example of the table , we identified that “體力 力氣” has the highest frequency, and we select “體力 力氣” as the most appropriate sense.

4. Similarity computation

In this step, we calculate similarity between the sentence containing the target word and the description of each target word in the WordNet dictionary. The similarity computation between the two parts is due to the Pirró’s algorithm (Pirró 2009). The formula for calculating sentence similarity between sentences X, Y is as shown in Eq. (1)

$$Sim_{sentence}(X,Y) = \frac{\sum_{i=1,j\in Y}^{|X|} \max \ Sim_{word}(X_i,Y_j) + \sum_{i=1,j\in X}^{|Y|} \max \ Sim_{word}(Y_i,X_j)}{|X|+|Y|} \tag{1}$$

where X, Y are sentences, $Sim_{word}(x, y)$ is to calculate similarity between two words, as defined in Eq. (2) .

$$Sim_{word}(x,y) = IC(msca(x,y)) - IC(x) - IC(msca(x,y)) - IC(y) - IC(msca(x,y)) = 3 \cdot IC(msca(x,y)) - IC(x) - IC(y) \quad (2)$$

The example of sentence similarity and word similarity is shown as in Table 3 and Table 4, where 'They didn't have much energy' is the sentence with the target word 'energy'.

Table 3. Similarity between target sentence and word definition

	Sample sentence	Noun in sentence	Similarity
1.	They didn't have much energy a healthy capacity for vigorous activity	"energy" "capacity", "activity"	0.8555
2.	They didn't have much energy The capacity of a physical system to do work	"energy" "capacity", "system", "work"	0.7229
3	They didn't have much energy enterprising or ambitious drive	"energy" "drive"	0.8531
4	They didn't have much energy An imaginative lively style	"energy" "style"	0.5047

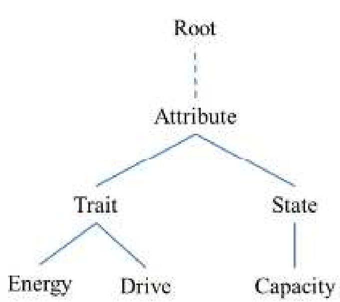
Table 4. Examples of word similarity

	Sample word	Similarity
1	"energy" and "capacity" "energy" and "activity"	0.5856 0.8555
2	"energy" and "capacity" "energy" and "system" "energy" and "work"	0.5856 0.3227 0.7229
3	"energy" and "drive"	0.8531
4	"energy" and "style"	0.5047

Table 3 shows that the similarity between "energy" and other trait creature is higher than the similarity between "energy" and other non-trait creature. The IC of the concept c is defined as:

$$IC(x\,) = 1 - \frac{\log(hypo(x)+1)}{\log(max_{con})} \quad (3)$$

where hypo(x) is the number of hyponyms of a given x, and max_{con} is a constant that indicates the total number of concepts in the considered taxonomy. The example IC calculation is shown in Figure 7 (Wu 2011).



(a)

Concept	IC
Root	0
Attribute	0.05
Trait	1
State	0.68
Energy	0.68
Drive	1
Capacity	1

(b)

Figure 7. The example of IC calculation.

5. The most frequent sense

Many studies (Fernandez-Amoros 2011; Gass 1988) indicate that the most frequent sense has the highest probability of the sense of the word. In the WordNet dictionary, the first sense is the most frequent one. The sample is shown as in Figure 7. In most articles, the most common translation of the target word is the most appropriate translation.

In this study, we use the WordNet dictionary because the other public electronic dictionaries do not provide more information than it for users.

6. Ranking of the senses

In the final step, there are two parts. The first is combination of the three weighting parts. The second part is to sort the results from the outputs of the first part. The process is described as follows:

The first is to combine co-occurrence degree, similarity degree between sentences and the most frequent sense. Co-correlation alone yields the disambiguation result below expectation. We compensate for this shortcoming by similarity extent between context sentence and the definition of the sense. The process is shown in Figure 8.

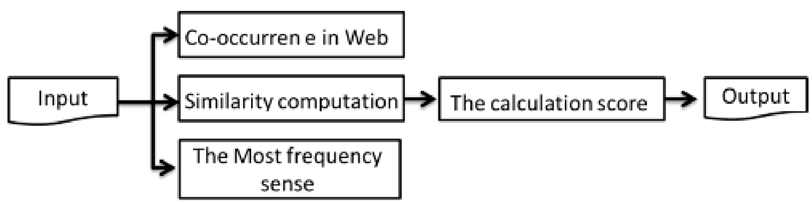


Figure 8. Calculation of score for determining the most appropriate sense

The combination process is described in detail as follows.

(1) Similarity computation:
In this step, we sort the results of similarity computation.

(2) Co-occurrence in Web:
We capture co-occurrence frequency based on the most frequent sense and similarity computation of the top three senses. Moreover, we normalize the results. The formula for normalized result can be specified as:

$$N = \frac{\text{Each of candidate common occurrent frequency}}{\text{Sum of candidate common occurrent frequency}} \tag{4}$$

(3) The most frequent sense:
In this step, we compare the candidate sense with the first sense in the WordNet dictionary to determine whether the candidate is the most frequent one.

(4) The calculation score:
The step is to calculate the integrated score. The formula can be specified as

$$Score = 0.5 * sim + 0.25 * N + 0.25 * F.$$

$$F = \begin{cases} 1, & \text{If it is the first sense in WordNet dictionary} \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

where *sim* is similarity computation by using Eq. (1), N is the normalized co-occurrence frequency in Web and F indicates whether it is the first sense in the WordNet dictionary.

The second is to sort the sense according to the *scores* decreasingly. The results allow learner to select the most appropriate sense based on the ranking list [3]. The sample of translation of "energy" ranking list is shown in table 5.

Table 5. The examples of translation of "energy" ranking list

Translation	similarity	co-occurrence	The most frequency sense	score
元氣 體力 活力	0.8555	5,720 (0.0173)	True	0.6821
能源 能量	0.6517	153,000 (0.4540)	False	0.4393
精力 精神 活力	0.7229	171,000 (0.5186)	False	0.4911
體力 力氣	0.5388	190,000	False	

IV. EXPERIMENTAL RESULTS

In this section, the experiment evaluates performance of translation of vocabulary. We selected the experimental dataset which includes four articles from an English class.

4.1 Translation of vocabulary

In this section, we perform WSD experiment and compare LAE with four methods, which are Pirro similarity (Pirró, 2009) of the target sentence, Pirro similarity of the context sentence, Co-occurrence in Web, and the most frequency sense. Pirro similarity is measured by exploiting a feature-based theory of similarity and translating into the information theoretic domain. The co-occurrence in Web method exploits only the information of co-occurrence frequency. The most frequency sense method considers the most frequency sense as the sense of the target word.

We capture seventy words of the highest frequency from each of the four articles. Proper nouns and non-words are discarded. Therefore, we collect a total of 279 words for the experiment. Among them, 29 words are of one POS with one sense, 91 words are of one POS with multiple senses, and 159 words are of Multiple POS with multiple senses. The experimental results are shown in Table 6 and Table 7.

Table 6. The word sense disambiguation accuracy of considering top one word

Method	One POS with one sense	One POS with multiple sense	Multiple POS with multiple senses
Pirro's (Similarity of the target sentence)	29 (100.0%)	28 (30.77%)	50 (31.45%)
Pirro's(Similarity of the context sentence)	29 (100.0%)	34 (37.36%)	49 (30.82%)
Co-occurrence in Web	29 (100.0%)	31 (34.07%)	50 (31.45%)
The most frequent sense	29 (100.0%)	75 (82.42%)	121 (76.10%)
LAE	29 (100.0%)	75 (82.42%)	124 (77.99%)

Table 7. The word sense disambiguation accuracy of considering top three words

Method	One POS with one sense	One POS with multiple sense	Multiple POS with multiple senses
Pirro's Similarity of the target sentence	29 (100.0%)	66 (72.53%)	94 (59.12%)
Pirro's Similarity of the context sentence	29 (100.0%)	70 (76.92%)	94 (59.12%)
Co-occurrence in Web	29 (100.0%)	71 (78.02%)	94 (59.12%)
The most frequent sense	-	-	-
LAE	29 (100.0%)	80 (87.91%)	131(82.39%)

Table 6 shows the WSD accuracy of top-one sense for vocabulary reading whether it is the most appropriate sense. Table 7 shows the accuracy of top-three senses reading whether the top three contain the most appropriate sense. The results demonstrate that our method is more effective than the other four methods.

Experimental results showed that the accuracy of words having multiple POS with multiple senses is lower than that of words having one POS with multiple senses. We analyzed the results and found that some of the words having multiple POS with multiple senses were incorrectly marked by the POS tagger and therefore yielded incorrect outcome of disambiguated sense. For example, the target word "mean" was tagged "adjective" by the POS tagger. However, the correct result shall be a "verb". Therefore, it leads to incorrect disambiguation in the latter phase.

V.CONCLUSION

In this paper, we have proposed an English-learning Assistance e-book (LAE) based on word sense disambiguation (WSD) and personal learning notes, which can help learners improve their reading comprehension skill. The experimental results indicate that disambiguation accuracy of LAE is better than that by Pirro Similarity of the target sentence, Pirro Similarity of the context sentence, Co-occurrence in Web and the most frequent sense. Especially in multiple POS with multiple senses results, LAE is better than the most frequent sense. In addition, LAE provides personal learning notes which the learner can record personal study notes and review anywhere anytime.

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應用行動學習與詞義消歧技術於英文學習電子書

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摘要

在數位化時代中，電子書儼然成為熱門趨勢之一，如何建構一套具吸引力的電子書系統已成為現今重要議題。在全球化的環境中，英文能力扮演著重要的角色，然而有許多學習者受限於時間及地點的限制，無法有效率的提升自我英文能力。因此本研究提出一個應用行動學習以及詞義消歧技術所發展的英文學習輔助電子書，此電子書的兩大特色為個人學習註記及決定最適合文章文義的英文單字翻譯。實驗結果顯示單字翻譯精準度優於現存的方法。本研究所提出的英文學習輔助電子書確實可以幫助學習者有效率的學習英文。

關鍵字：英文輔助學習、詞義消歧、行動學習、電子書