行政院國家科學委員會專題研究計畫 成果報告

校園內支援情境脈絡學習之個人化行動英語學習系統發展與研究

研究成果報告(精簡版)

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行政院國家科學委員會專題研究計劃成果報告

校園內支援情境脈絡學習之個人化行動英語學習系統發展與研究

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摘要

隨著科技不斷的進步與創新，許多新的學習理論與技術相繼被提出，使得傳統的學習模式有了很大的改變。由於政府在無線網路設施上的積極建設，以及行動裝置如 PDA、智慧型手機的普及，利用行動裝置進行行動學習已被視為是一種新穎且有效率的學習模式，然而又隨著無線網路定位、RFID、紅外線及超音波等位置感知技術的發展，更進一步讓情境脈絡感知之無所不在學習成為未來可能的一種新型態學習模式。藉由無所不在的情境感知與行動計算，學習者可以在任何時間、任何地點，透過情境感知技術的輔助進行學習，能讓學習者除了擁有行動學習的便利之外，也可以同時與學習情境作更緊密的結合。

另一方面，由於英語已成為國際共通的語言，在邁向國際化、開拓世界觀的潮流帶動之下，英語學習已經成為非英語系國家的全民運動。因此，發展有效協助英語學習的工具亦是英語教育領域的重要議題。發展個人化、結合學習情境之無所不在英語學習模式，可以帶給民眾最符合需求的行動學習服務。故本計劃研究發展「校園內具支援情境脈絡學習之個人化行動英語學習系統」，藉由校園無線網路發展偵測學習者位置的定位技術，配合學習者的學習時間、個人學習特質與學習能力等情境資訊，依據學習者和週遭環境及個人化學習機制的互動狀況，獲取適性化的英語學習內容，提昇語言學習的樂趣與成效。

關鍵字：情境脈絡學習、無線網路定位、行動學習、個人化學習、英語學習

Abstract

Compared to traditional classroom learning, current learners have more choices since the progress of learning technologies brought up many new learning theories and novel learning modes. With the rapid growth of wireless, the mobile learning by the handheld devices, such as PDA, smart phone etc., has been gradually considered as a novel and effective learning form. Meanwhile, advances in wireless positioning techniques, RFID, infrared and ultrasound sensing techniques allow learners to further establish ubiquitous learning environment. Ubiquitous learning, or pervasive learning, supports learners to learn at any time and any place through context-aware sensing techniques.

In addition, English has been an international language, and learning English has become a trend that cannot be ignored specially in non-native English speaking countries. Therefore, how to develop an effective assisted learning tool becomes an important issue in English learning. Developing personalized context-aware ubiquitous learning environment can bring the most desired service of English learning to individual learners for promoting English learning. Accordingly, this project proposes a personalized ubiquitous learning system based on wireless positioning techniques for supporting effective English learning in campus. This system exploits appropriate context based on the detected location of learner, learning time, and individual abilities etc. to adapt their learning contents toward learners for promoting the learning interests and abilities.

Keywords: Context-aware ubiquitous learning, Wireless positioning, Mobile learning, Personalized learning, English learning

1. Introduction

Ubiquitous learning enables learners to learn at anytime, anywhere through wireless network environment using context-aware techniques [1][2]. The so-called "context-aware" requires the detection of user's context information and provides different services according to different contexts [3][4]. Dey [3] proposed that four main types of contextual information are: identify, time, activity, and location. Wireless Local Area Network (WLAN) can provide location information in the indoor environments. Hence, the WLAN positioning techniques enable the development of the context-aware ubiquitous learning that can provide the learning contents associated to the learning context in this study.

"The situational learning approach" proposed that context is an important factor in the language learning process and it can enhance the learner's learning interests and efficiency [5]. The meaningful knowledge is constructed only when learning process integrates with society culture and life-context. Therefore, this study proposed a personalized context-aware ubiquitous English learning system to make use of existing WLAN infrastructure and carry out the location detection, such that the adaptive learning contents are recommended to individual learners based on their learning locations, learning time, learning abilities and leisure time.

2. System Design and Architecture

2.1. System architecture

The proposed system aims at enhancing learners' impression and interests of learning English vocabulary and increasing the performance of English vocabulary based on the situational learning approach supported by WLAN positioning techniques. The system architecture is illustrated as Fig. 1. First, the learner locating agent detects the learner's location based on the WLAN positioning techniques in a schoolyard environment. According to the learner's location, the context analysis agent analyzes the learning requirements of individual learner in collaboration with the personal preference database and the context database, and then determines the learning parameters consistent with the context. Then, the English learning materials searching agent discovers the suitable learning materials from the classified English courseware database according to the analyzing result of the context analysis agent. Finally, the content delivery agent and message delivery agent organize the English materials and send the learning contents to individual learners.

2.2. Context-aware detection techniques

Detecting the context of location is rather important function in this study. This study employed the WLAN positioning techniques to develop positioning service for English vocabulary learning. The back-propagation (BP) neural network is used to construct a classification model for mapping signal strength features into corresponding locations in this study. The signal strength of each AP is served as the input and the outputs represent the corresponding locations. The experiment result shows that the accuracy rate of positioning is up to 92.7%.

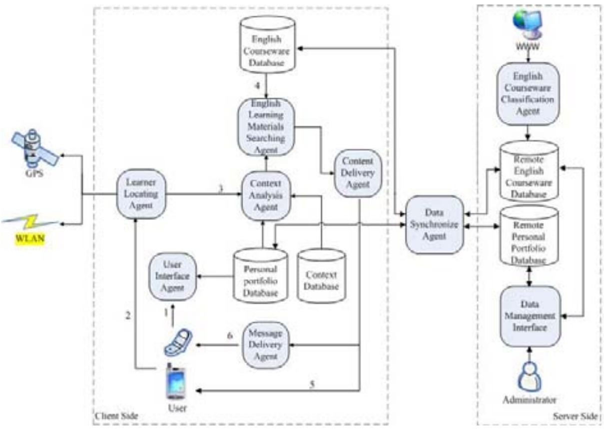


Figure 1. The system architecture

2.3. Recommending context-aware English vocabulary

2.3.1. Selecting location-based English vocabulary. Location is the most important factor in the context-aware system. In this work, the vocabularies corresponded to current location will be provided to individual learners. For instance, some words such as exam, student, assess, etc. will be learned if learners is in a classroom. Thus, the first step of vocabulary recommendation strategy is to select vocabularies based on the learner's location. Next, the following subsection shows how to decide appropriate vocabulary according to learner vocabulary abilities using the maximum information function.

2.3.2. The maximum information strategy. In Item Response Theory (IRT) [6], the maximum information approach emphasizes that each vocabulary with corresponding difficulty parameter exhibits different information to a learner with corresponding vocabulary ability. Vocabularies with high information values are more suitable for the learner. In this work, the maximum information function is applied to recommend appropriate vocabularies to individual learners. The maximum information function is formulated as follows:

$$I_j(\theta)=\frac{(1.7)^2}{\left[e^{1.7(\theta-b_j)}\right]\left[1+e^{-1.7(\theta-b_j)}\right]^2} \qquad (1)$$

where $I_j(\theta)$ is the information value of the j^{th} English vocabulary at a level below their ability level θ, b_j is the difficulty parameter of the j^{th} English vocabulary.

2.3.3. Evaluating the score of time characteristic. The time characteristics of selected vocabularies are also considered to obtain a score in order to further integrate with the information value mentioned above. Considering time characteristic score aims to find out vocabularies that conform to the learning time when a learner proceeds a learning activity. In this study, the score of time characteristic is computed based on fuzzy weight. The fuzzy membership functions of each time characteristic are heuristically determined.

The score of time characteristic and the information function value are denoted as ST_j and I_j, respectively. The final score S_j of the j^{th} English vocabulary can be measured by the following formulation:

$$S_j = w \times I_j + (1-w) \times ST_j \qquad (2)$$

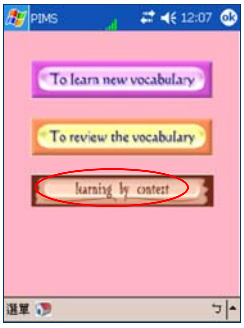
where w is an adjustable weighting factor reflecting the relative importance of learner's ability and the time characteristic.

After calculating the corresponding final score, the vocabularies with relatively high score values among selected vocabularies will be delivered to individual learners.

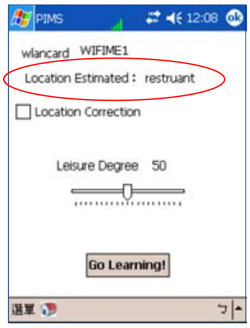
2.3.4. Estimating the amount of learning words. If a learner wants to learn some new words, he/she may have different amount of available time each time. The context analysis agent decides the amount of learning vocabularies based on the learner's ability and leisure time inferred by a pre-designed fuzzy rule knowledge base.

3. The Implemented System on PDA

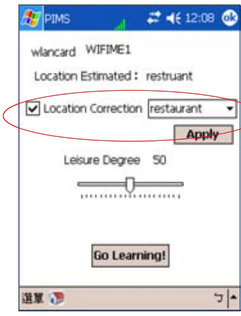
First of all, the menu of vocabulary learning system is shown as Fig. 2(a). When a learner would like to perform the context-aware learning process, he/she can click the button of "learning by context" and the learner locating agent will then begin to sense the learner's location. Figure 2(b) reveals the positioning result and the system could remind learner to adjust the current leisure degree for inferring appropriate number of vocabularies for learning. Figure 2(c) shows the additional functionality for correcting location information based on learner feedback responses and learners can make location correction by a prior list of location information.



(a) The menu of learning



(b) The result of location estimation



(c) The functionality of location correction

(d) The learning content at restaurant on December 21

(e) The learning content at restaurant on February 25

(f) The corresponding test of the learned vocabulary

(g) The test result

Figure 2. The implemented learning system

After the learner selects to go on with learning process, the system will discover suitable vocabularies based on the learner's ability, the leisure degree, the location and the current time. Figures 2(d) and (e) show the recommended vocabulary and the number of learning words. Maybe learners locate at same place "restaurant", Figs. 2(d) and (e) display that the system can recommend appropriate vocabularies to individual learners according to different learning time. Thus, in Fig. 2(d), the word with the characteristic of Christmas has high priority because the learning time is close to Dec. 25th. However, Fig. 2(e) shows when the learning time is on Feb. 25th, the word characterized by Christmas is no longer ranked as the first priority word owing to ending of Christmas day. After studying recommended vocabularies, the learner can perform the corresponding vocabulary test to re-examine the individual vocabulary ability and the test results will be presented to the learner. Figures 2(f) and (g) show the test process and the test result.

4. Experimental Design

To evaluate the learning performance of the proposed personalized context-aware English vocabulary learning system, 36 tenth grade students studying in the Affiliated High School of National Chengchi University were invited to participate in this experiment. The students were randomly assigned to either the experimental or control groups. Each group contained 18 students with the average age being around 16 years old. Each group contained 9 males and 9 females. A nonequivalent pre-test-post-test group based on a quasi-experimental design was employed to analyze the learning performance of the proposed system.

Before performing the experiment, all participants received a 100 minute training course in operating PDA and using the proposed English vocabulary learning system with or without context-aware service. In this experiment, the experimental group learned the recommended vocabulary with the support of the proposed context-aware service, while the control group learned the same vocabulary without such support. The vocabulary learning activity of two groups lasted two weeks. Both the learning modes performed the pretest and posttest for comparing the difference in learning performance before and after learning using PDA. To provide a context-aware service for English vocabulary learning in the experimental schoolyard, 12 campus locations in the Affiliated High School of National Chengchi University were chosen to provide a location-based context-aware service. The students of the experimental group were free to go to these places at anytime and the proposed system could recommend suitable English vocabulary related to learning environment to individual learners for English vocabulary learning. Figures 3 and 4 illustrate the learning scenario of the experimental group students that learned English vocabulary via the proposed personalized vocabulary learning system with context-aware service in the library and garden, respectively.

Figure 3. Vocabulary learning in the library using the proposed system

Figure 4. Vocabulary learning in the garden using the proposed system

5. Research Outcomes

This study proposes a personalized context-aware ubiquitous English vocabulary learning system, which can recommend appropriate English vocabulary associated with providing context-awareness information to individual learners, to support effective English vocabulary learning. The proposed system developed a learner location estimation scheme based on back-propagation neural networks to support personalized context-aware ubiquitous English vocabulary learning. The accuracy rate in detecting leaner location exceeds 92%, which is sufficient to aid situational English vocabulary learning. The proposed personalized context-aware ubiquitous English vocabulary learning system was successfully implemented on PDA to facilitate a seamless ubiquitous English learning environment without constraints of time or place. Moreover, a nonequivalent pre-test-post-test group based on the quasi-experimental design was performed in a high school to assess learner learning performance after using the proposed context-aware ubiquitous English vocabulary learning system. The statistical results (F=5.785, sig of F=0.022) revealed that the learning performance of learners who used the personalized English vocabulary learning system with context-aware service is significant based on the assessment of the pretest and posttest, and exceeds the performance of learners who used the learning system without context-aware service according to ANOCA analysis. Additionally, the questionnaire analysis indicated that over 50% of learners achieve satisfactory learning experiences after using the proposed context-aware ubiquitous English vocabulary learning system. Furthermore, up to 72.2% of learners prefer English learning systems with context aware-service after experiencing two learning modes.

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行政院國家科學委員會補助國內專家學者出席國際學術會議報告

97 年 11 月 26 日

報告人姓名	陳志銘	服務機構及職稱	國立政治大學圖書資訊與檔案學研究所副教授
會議時間地點	97 年 9 月 21~24 日 中國成都市 China, Chengdu	本會核定補助文號	NSC96-2520-S-004-001 計劃補助
會議名稱	(中文)2007 年 IEEE 人工腦學與智慧型系統國際研討會 (英文)2008 IEEE International Conferences on Cybernetics & Intelligent Systems		
發表論文題目	（中文）在網路合作式學習環境中探勘互動學習社會網路推薦合適學習伙伴 （英文）Mining Interactive Social Network for Recommending Appropriate Learning Partners in a Web-based Cooperative Learning Environment		

一、 參加會議經過

本次會議旅程是經由雄獅旅行社代為訂購機票及安排住宿事宜，經由旅行社安排，個人於九月二十日上午搭乘長榮航空班機飛往香港赤臘角國際機場轉機，再搭乘港龍航空班機抵達成都雙流國際機場，抵達雙流國際機場後即搭乘飯店巴士至住宿旅館。接下來即為為期將近五天的參加會議及參訪行程。會議結束後，個人於當地時間九月二十五日下午由成都成雙流國際機場搭乘港龍航空班機飛抵香港轉長榮班機返國，過程相當順利且圓滿的完成整個會議的相關行程。

二、 與會心得

(一)深入了解國際間智慧型系統之發展近況

此次大會由中國四川電子科技大學主辦，會議地點在 Sheraton Chengdu Lido Hotel，並由國際電機電子工程學會贊助，投稿論文來自世界 36 個國家共計 950 篇論文，大會也安排了幾場重要的 Keynote Speech，其中中國大陸發表的論文佔有極高的比例，這或許是主辦國的因素，但也可以看出中國大陸學術發展的盛況。此外，這次參與的人數受到四川地震的影響頗大，與會人數因此而減少，但參加會議人士討論熱絡，堪稱一次學術界的盛會，內容涵蓋極廣，本人參加會議所獲取之新知對個人之未來研究幫助極大。

(二)結交國際學者

經由參加會議吸收許多新知識，並於 Coffee Break 時間，結交許多國際學者，有的係邀稿，有的係吸收會員，有的純粹作學術交流，也有的則閒話家常。在會議其間也遇到許多中國大陸天津大學及四川大學的教授，可能大家語言相同，很容易便開始由英文轉換為中文進行交談，也瞭解進幾年中國大陸高等教育及研究發展近況，大家也交換名片相約於會後繼續保持密切聯繫，感覺收穫良多。

(三)訓練英語聽講能力及體驗四川文化及風土民情

個人已累積多次出國發表論文經驗，此次與台灣師範大學應用電子科技學系洪欽銘教授一同與會發表論文，另外也藉由此次會議的空閒時間，參訪四川大學、四川電子科技大學、貓熊基地、都江堰、樂山大佛等名勝，也親自體驗四川聞名的飲食文化，是一次成功且難得的經驗，個人覺得獲益良多。

三、 建議

(一)國際間在智慧型系統相關領域的研究發展與應用進步快速，例如結合生理資訊進行情緒識別與情境感知等領域的智慧型系統研究，國內學界與業界應加強緊密之結合，以產學合作模式，以達相輔相成之效。

(二)國內宜加強英語聽講之教學，或者在校園內建立更好的的英語學習環境，如此則未來學人參加國際會議即可得心應手，也增加台灣的國際能見度。此外，在國外也感受到近幾年中文越來越受到重視，因此國內有必要充份運用我們在中文上的優勢，發展中文相關的數位學習內容。

四、 攜回資料名稱及內容

此次參加會議，大會準備了大會議程表、論文集及許多明年相關國際研討會的 Call for Paper 資料，個人也攜回台灣作為明年參加會議的參考。例如 2009 年的 IEEE International Conference on Cybernetics & Intelligent Systems 及 2009 年 IEEE International Conference on Systems, Man, and Cybernetics 等。這些即將舉辦的國際研討會將作為個人明年出國發表論文的目標。

Mining Interactive Social Network for Recommending Appropriate Learning Partners in a Web-based Cooperative Learning Environment

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Abstract—**In Web-based cooperative learning environments, peer-to-peer interaction often suffers from the difficulty due to lack of exploring useful social interaction information, so that peers cannot find appropriate learning partners to make an effective cooperative learning. This problem easily results in poor learning outcomes in Web-based cooperative learning environments. Generally, learning partners assigned by instructors cannot ensure to compose suitable learning groups for individual learners in cooperative learning environments. Inappropriate learning partners not only easily lead to poor learning interaction and achievement, but also lose the meaning of cooperative learning. As a result, this study presents a novel scheme of mining social interactive networks for recommending appropriate learning partners for individual learners in a cooperative problem-based learning environment. The preliminary experimental results reveal that the proposed scheme provides likely benefits in terms of promoting learners' learning interaction and learning performance in cooperative learning environments.**

Keywords—**cooperative problem-based learning, social network analysis, learning partner recommendation**

I. INTRODUCTION

With the rapid development of the Internet and the popularization of World Wide Web, lots of people tend to transfer their social activities from real human interaction to virtual social network interaction. Most social network services are primarily web based and provide a collection of various ways for users to interact, such as chat, messaging, email, video, voice chat, file sharing, blogging, discussion groups, and so on [1]. In recent years, more and more studies paid attention to social network analyses [2-4] and many webs sites [5] provided social functionalities to benefit the learning interactions between learners. These social interaction mechanisms encourage a large amount of users to cooperatively participate in web learning activities. A social network is considered as a group of people, an organization or social individuals which are connected by social relations such as friendships, cooperative relations, or informative exchange [3]. Basically, the focuses of social network analysis lie on the analyzing patterns of relationships among people, organizations, states and such social individuals [2].

Cho *et al.* [6] indicated that theoretically there are abundant discussions emphasizing the value and the impact of social networks in the studies of organizational learning, knowledge management, and distance learning; however, few studies have actually examined the "origins" or "outcomes" of social networks in actual Computer-Supported Collaborative Learning (CSCL) or Cooperative Work (CSCW) settings. Furthermore, this study [6] also indicated social networks have significant impact on learning performance in a CSCL setting, since learning activities in such a collaborative environment are predominantly based on communication, social interactions, and coordination among distributed learners. Moreover, Tomsic and Suthers's study [7] investigated the social network structure of booking officers at the Honolulu Police Department and how the introduction of an online discussion tool affected knowledge about operation of a booking module. This study found that discussion tool provides benefit in terms of increasing knowledge in a cooperative discussing learning environment.

Although learners are grouped together for learning activities in cooperative learning environments, they often could not find appropriate learning partners to each other for conducting effective learning due to lack of complete social interaction information or they are assigned inappropriate learning partners by instructors. Therefore, this study presents a novel mining scheme of cooperative social networks to explore the active degrees and interactive relationships between learners in a cooperative problem-based learning environment. The exploring social information can be applied to enhance the learning interaction and performance in cooperative learning environments via revealing the social position ranking of individual learners and recommending appropriate learning partners.

II. EXPERIMENTAL ENVIRONMENT DESCRIPTION

This section explains the experimental environment for mining social networks. Figure 1 shows the system diagram of the employed cooperative problem-based learning system with mining social interactive network mechanism. The employed system is consisted of the cooperative problem-based learning system, social network analysis module and three databases. The cooperative problem-based learning system used in the study can provide a friendly learning environment, which is convenient to cooperatively solve a target problem assigned by instructors. All interaction information from learners' cooperative learning processes is stored in the learning record database. The social network analysis module aims to explore learners' social interaction relationships in the cooperative problem-based learning system based on the interaction information stored in the learning record database. Furthermore, the learning partner recommending agent can recommend appropriate learning partners for individual learners according to the results of mining learners' interaction relationships in the cooperative problem-based learning system.

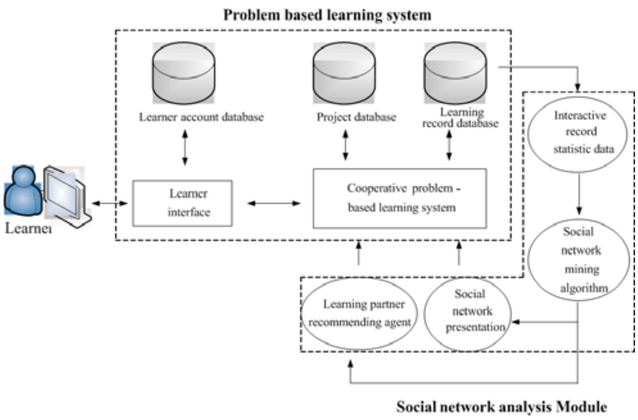

Figure 1. System diagram of the employed cooperative problem-based learning system with mining social interactive network mechanism

III. THE PROPOSED SCHEME OF MINING INTERACTIVE SOCIAL NETWORKS IN A COOPERATIVE PROBLEM-BASED LEARNING ENVIRONMENT

This section presents how the learners' interactive records stored in the learning record database can be used to explore social interaction relationships in the employed cooperative problem-based learning environment.

A. Social Networks in the Employed Cooperative Problem-based Learning Environment

Next, this study defines three interactive relationships between learners in the employed cooperative problem-based learning environment. Figure 2 illustrates an example to explain these three considered interactive relationships. In this example, we consider the interactive relationships of the learner A with the other three learning peers B, C, and D. The interaction initiated by the learner A to any peers is termed as "out-degree interaction". Similarly, the interaction initiated by any peers to the learner A is termed as "in-degree interaction". The bidirectional interaction with the learner A is termed as "linked interaction". Taking Fig. 2 as an example, the in-degree interaction value of the learner A is 2 because both the learners C and D initially interact with the learner A. The out-degree interaction value of the learner A is 2 because the learner A actively interacts with both the learners B and C. Moreover, the linked interaction value of the learner A is 1 because the learner A has bidirectional interaction with the learner C. The mathematical definitions for calculating three proposed interaction values are further explained in the following section.

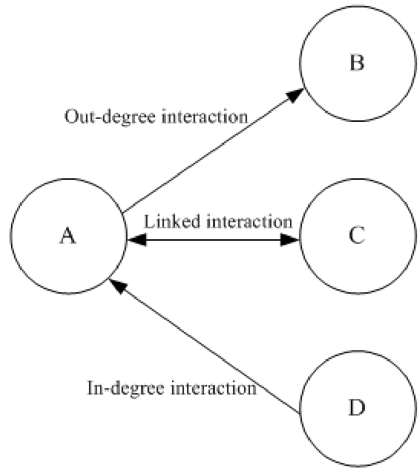

Figure 2. Interactive relationships between learners in the employed cooperative problem-based learning environment

B. Social Measures for Mining Interactive Social Networks in the Employed Problem-based Cooperative Learning Environment

This section mathematically defines five social measures for mining interactive social networks in the employed problem-based cooperative learning environment. They are detailed as follows:

(1) In-degree interaction value: The number of learners who actively interact with a certain learner in the cooperative problem-based learning environment. The in-degree interaction value can be formulated as

$$R_{In(n)} = \sum_{m=1}^{t} C_{m,n} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

where $R_{In(n)}$ stands for the in-degree interaction value of the n^{th} learner, $C_{m,n}$ is set to 1 if the m^{th} learner actively interacted with the n^{th} learner; otherwise, $C_{m,n}$ is set to 0, and t is the total number of learners excluding the n^{th} learner in the cooperative problem-based learning environment.

(2) Out-degree interaction value: The number of learners who accept interactive request from a certain learner in the cooperative problem-based learning environment. The out-degree interaction value can be formulated as

$$R_{Out(n)} = \sum_{m=1}^{t} C_{n,m} \text{ ………………...(2)}$$

where $R_{Out(n)}$ is the out-degree interaction value of the n^{th} learner, $C_{m,n}$ is set to 1 if the m^{th} learner accepts interactive request from the n^{th} learner; otherwise, $C_{m,n}$ is set to 0, and t is the total number of learners excluding the n^{th} learner in the cooperative problem-based learning environment.

The in-degree and out-degree interaction values represent popular and initiative degrees of a learner in the cooperative problem-based learning environment, respectively. Based on the in-degree and out-degree interaction values, this study further divides learners into four interactive types in the cooperative problem-based learning environment: Hub, Source, Sink and Island [2]. TABLE I illustrates the four interactive types based on interactive characters of individual learners in the cooperative problem-based learning environment.

TABLE I. FOUR INTERACTIVE TYPES BASED ON INTERACTIVE CHARACTERS IN THE COOPERATIVE PROBLEM-BASED LEARNING ENVIRONMENTS

Interactive type	Interactive character
Hub	Both in-degree and out-degree interaction values are high
Source	In-degree interaction value is low and out-degree interaction value is high
Sink	In-degree interaction value is high and out-degree interaction value is low
Island	Both in-degree and out-degree interaction values are low

(3) Linked interaction value：The number of learners who have bidirectional interaction with a certain learner in the cooperative problem-based learning environment. The linked interaction value can be formulated as

$$R_{Iv(n,m)} = \sum_{m=1}^{t} \left(C_{m,n} \times C_{n,m} \right) \text{....................(3)}$$

where $R_{Iv(m.n)}$ is the linked interaction value of the n^{th} learner with the m^{th} learner, $C_{m,n} \times C_{n,m}$ is equal to 1 if the bidirectional interaction exists between the n^{th} learner with the m^{th} learner; otherwise, $C_{m,n}$ is equal to 0, and t is the total number of learners excluding the n^{th} learner in the cooperative problem-based learning environment.

The linked interaction value represents the active degree of a learner in the cooperative problem-based learning environment. Next, this study uses the linked interaction value to compute the interactive score of each learner based on four defined interactive intervals in the cooperative problem-based learning environment.

(4) Interactive score: The interactive score is viewed as a weight score of interactive level between a learner with the other learning peers in the cooperative problem-based learning environment. According to quarter method of the statistics, this study divides all learners into four interactive intervals and assigns various weight scores for different interactive levels based on the linked interaction values of all learners. The Interactive score can be formulated as

$$I_n = \begin{cases} 4, R_{Iv} \geq R_{(\text{top 25\% high})} \\ 3, R_{(\text{top 50\% high})} \leq R_{Iv} \leq R_{(\text{top 25\% high})} \\ 2, R_{(\text{top 75\% high})} \leq R_{Iv} \leq R_{(\text{top 50\% high})} \\ 1, R_{Iv} \leq R_{(\text{top 75\% high})} \end{cases} \text{ ………(4)}$$

where I_n is the interactive score of the n^{th} learner, $R_{(\text{top 25\% high})}$ is the interactive interval whose learners' linked interaction values are the top 25% high, $R_{(\text{top 50\% high})}$ is interactive interval whose learners' linked interaction values are the top 50% high, and $R_{(\text{top 75\% high})}$ is the interactive interval whose learners' linked interaction values are the top 75% high.

The learners categorized in the interactive intervals with high linked interaction value are easier to interact with peers than the learner categorized in the interactive intervals with low linked interaction value. Basically, these learners with high linked interaction value can be viewed as the Hub interactive type. On the other hand, the learners with low linked interaction value can be viewed as the Island interactive type. According to the interactive level, this study assigns various interactive score from 4 points to 1 point for further evaluating the social score of each learner in the cooperative problem-based learning environment.

(5) Social score：The social score represents the social position of a leaner in the cooperative problem-based learning environment. Suppose the n^{th} learner interacts with the m^{th} learner. The social score is formulated as

$$S_n = \sum_{m=1}^{t} \left(C_{m,n} \times C_{n,m} \times I_m \right) \text{……………...(5)}$$

where S_n is the social score of the n^{th} learner in the cooperative problem-based learning environment, $C_{m,n} \times C_{n,m}$ is equal to 1 if the bidirectional interaction exists between the n^{th} learner with the m^{th} learner; otherwise, $C_{m,n} \times C_{n,m}$ is equal to 0, I_m is the interactive score of the m^{th} learner, and t is the total number of learners excluding the n^{th} learner in the cooperative problem-based learning environment.

Based on Eq. (5), when the n^{th} learner interacts with the m^{th} learner, the n^{th} learner can get the interactive score of the m^{th} learner, and the m^{th} learner can also get the interactive score of the n^{th} learner in the cooperative problem-based learning environment. Here, we further illustrate an example to explain how to compute social scores for individual learners in the employed cooperative problem-based learning environment.

Suppose that there are four learners A, B, C and D in the employed cooperative learning environment to perform problem-based learning. Figure 3 shows the interactive relationship graph of these four learners. Meanwhile, suppose the interactive scores of learners A, B, C and D are 3, 2, 4, and 1, respectively.

According to Eq. (5), the social score of the learn A is 2 because the learner A only exits the bidirectional interaction with the learner B. The social score of the learner B is 7 because the learner B simultaneously exists the bidirectional interactions with both the learners A and C. Similarly, the social scores of the learners C and D are 3 and 4, respectively. As a result, the ranking order of the social positions in this social network is B, D, C, and A. We can find that a learner may get lower social score than the others even he/she interacted with much more peers if he/she often interacted with peers who only have low interactive score. On the other hand, a learner may get higher interactive score than the others if he/she often interacted with peers who have high interactive score.

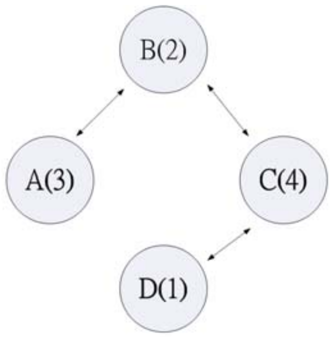

Figure 3. An example for illustrating how to compute social score in the employed cooperative problem-based learning environment (the number in the brackets represents the interactive score)

C. Cooperative Learning Partner Recommending Scheme based on the Results of Mining the Social Networks in the Employed Cooperative Problem-based Learning Environment

Many studies [6][7] had pointed out that the cooperative learning is an effective learning mode because it can promote learning interests and performance of learners via peer-to-peer interaction and assistance. However, how to find appropriate learning partners to further promote the learning performance of the cooperative learning is an essential research issue. Based on the observation mentioned-above, this study presents a cooperative learning partner recommending scheme based on the characters of individual learners in cooperative social learning networks. Basically, the learners who frequently interact with a certain learner are appropriate to be recommended to the learner as learning partners because they are familiar to each other. Furthermore, the learners who get a high social score are appropriate to be recommended to a certain learner as learning partners because they obtain high identification from most learners or they may be pleased or have excellent abilities to help the other peers to solve problems. Therefore, the study presents a cooperative learning partner recommending scheme based on a computed recommendation score which simultaneously considers two factors mentioned-above. The recommendation score for exploring appropriate learning partners can be formulated as

$$C_{n,m} = w \times \frac{S_m}{S_{\max}} + (1-w) \times \frac{R_{Iv(n,m)}}{R_{Iv(\max)}} \quad \ldots\ldots\ldots(6)$$

where $C_{n,m}$ represents the recommendation score of the m^{th} learner recommended to the n^{th} learner who would like to find appropriate learning partners in the cooperative problem-based learning environment, S_m is the social score of the m^{th} learner, $S_{\max}$ is the maximal social score among all learners, $R_{Iv(m.n)}$ is the linked interaction value between the n^{th} learner and the m^{th} learner, $R_{Iv(\max)}$ is the maximal linked interaction score among the learners who interacted with the n^{th} learner, and w is a adjustable linear combination weight.

IV. EXPERIMENTAL ANALYSIS

This section presents our experimental analyses. In our experiments, 34 learners of Nation Hualien University of Education who were studying in the Department of Chinese Language and Literature were invited to participate in cooperative learning in the employed cooperative problem-based learning system with mining social interactive network mechanism. These learners were assigned a target problem related to “how to design a teaching plan for computer integrated instruction”. Meanwhile, they must perform cooperative learning with peers to finish the problem-based learning processes in order to plan a teaching plan for the course of the computer integrated instruction during four weeks. These 34 learners generated a lot of social interaction records and these interaction records were stored in the learning record database. This study adopted these social interaction records to explore their social interaction networks. Figure 4 reveals the partial social position ranking of learners explored by the proposed scheme of mining interactive social networks in the cooperative problem-based learning environment. We found that instructor is the most active person in the interactive social networks because she often encouraged learners through sending messages during learning processes. In addition, learners also often sent messages to the instructor to ask assistance. If a learner would like to know his/her interactive relationships with the other peers, he/she only needs to click the personal icon and the system will present the corresponding interactive relationship diagram for him/her. Figure 5 displays the interactive relationship diagram of the number 72 learner with five learning peers in the cooperative problem-based social learning networks. Figure 5 reveals that the in-degree interaction value, out-degree interaction value, linked interaction value, interactive score, social score, and social position of the number 72 learner are 7, 19, 5, 4, 14, 4, respectively.

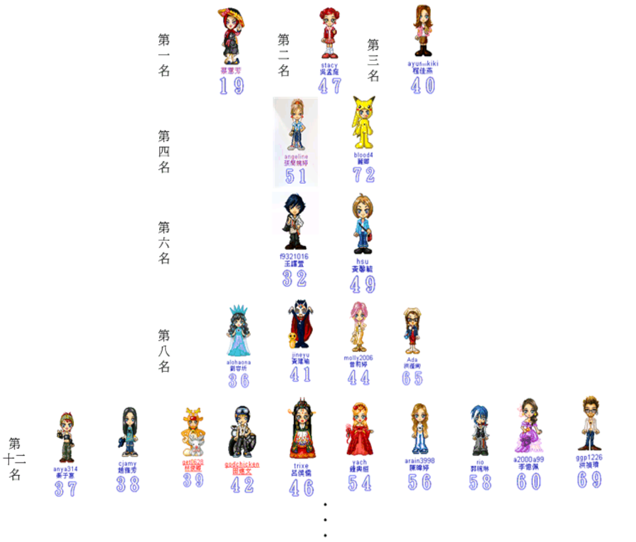

Figure 4. Illustration of a partial social position ranking in the employed cooperative problem-based learning environment

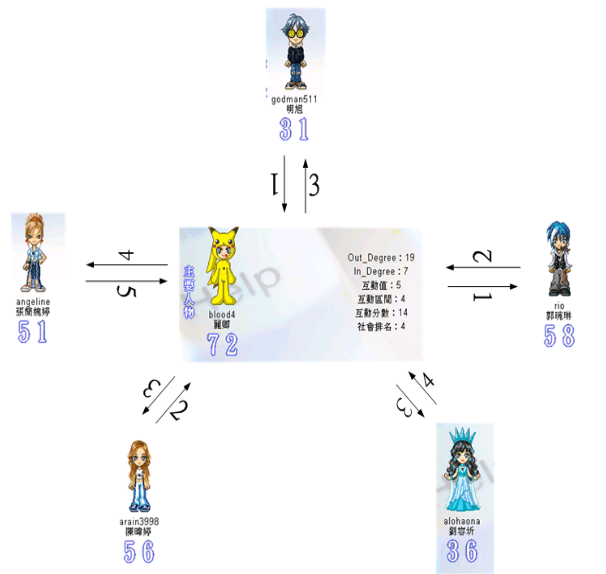

Figure 5. The interactive information of the number 72 learner in the employed cooperative problem-based learning environment

TABLE II illustrates the interactive information of instructor and three selected learners with various active levels in the cooperative problem-based learning environment. We found that the most active learner, moderate active learner, and most inactive learner are the number 47, 33, and 79 learners, respectively. Therefore, the number 47 learner can be viewed as the Hub type learner, and the number 79 learner can be viewed as the Island type learner. Based on the social information, instructor should encourage the number 79 learner to interact with the other peers in the cooperative problem-based learning environment.

Additionally, the proposed system can recommend those learners who had successfully passed current learning stage in the target problem assigned by instructor as the learning partners for those learners who still had not passed the current learning stage in the target problem. This is because these learners who had successfully passed current learning stage in the target problem can help those learners who still had not passed current learning stage in the target problem to solve learning problems.

TABLE II. INTERACTIVE INFORMATION OF INSTRUCTOR AND THREE SELECTED LEARNERS WITH VARIOUS ACTIVE DEGREES IN THE COOPERATIVE PROBLEM-BASED LEARNING ENVIRONMENT

Role / Comparison Item	Instructor	Number 47 learner	Number 33 learner	Number 79 learner
Out-degree interaction value	49	7	4	0
In-degree interaction value	18	8	3	0
Linked interaction value	17	9	2	0
Interactive score	4	4	2	1
Social score	44	20	6	0
Social position ranking based on social score	1	2	22	34

TABLE III displays the interactive scores of the number 72 learner with five different learners who have bidirectional interaction with the number 72 learner. TABLE IV shows the comparison of recommended learning partners for the number 72 learner under considering different linear combination weights. We found that the most appropriate learning partner for the number 72 learner is the number 51 learner when the adjustable linear combination weight w is set to 0.1 and 0.5. Actually, the number 51 learner has the highest linked interaction with the number 72 learner. On the other hand, we also found that the most appropriate learning partner for the number 72 learner is the number 47 learner when the adjustable linear combination weight w is set to 0.9. The social position of the number 47 learner is 2. In sum, setting a low linear combination weight tends towards recommending the learning partners who have high interaction relationship with the learner. By contrast, setting a high linear combination weight tends towards recommending the learning partners who have high social position in the cooperative problem-based learning environment.

This study also found that most learners prefer to be recommended the learning partners who have high linked interaction relationship with oneself. Probably, most learners are used to perform cooperative learning with familiar learners. From the point of view of learning, recommending the learning partners who have excellent personal characters or abilities is also a critical consideration. Therefore, how to determine an optimal linear combination weight for recommending appropriate learning partners has been considered as an urgent research issue in our future study.

V. CONCLUSION

This study proposes a novel scheme for mining social networks in an employed cooperative problem-based learning environment. In addition, this study also applies the results of mining social networks to present a learning partner recommendation scheme for recommending appropriate learning partners for individual learners. The preliminary experimental results show that exploring social positions of individual learners in the employed cooperative problem-based learning environment has high potential to encourage learners to interact with peers more actively. Moreover, recommending appropriate learning partners for individual learners provides likely benefit in terms of promoting the learning performance of individual learners in cooperative problem-based learning environments. In the future, the proposed scheme will be applied to real teaching scene to further demonstrate these two advantages mentioned-above.

TABLE III. THE INTERACTIVE SCORES OF THE NUMBER 72 LEARNER WITH FIVE DIFFERENT LEARNERS WHO HAVE BIDIRECTIONAL INTERACTION WITH THE NUMBER 72 LEARNER

	Number 31 learner	Number 36 learner	Number 51 learner	Number 56 learner	Number 58 learner
Number 72 learner	1	3	4	2	1

TABLE IV. COMPARISON OF RECOMMENDED LEARNING PARTNERS FOR THE NUMBER 72 LEARNER UNDER CONSIDERING DIFFERENT WEIGHTS

Adjustable weight / Recommending order	$w = 0.9$	$w = 0.5$	$w = 0.1$
The recommended learner with first priority	Number 47 learner (0.9)	Number 51 learner (0.85)	Number 51 learner (0.97)
The recommended learner with second priority	Number 51 learner (0.73)	Number 47 learner (0.5)	Number 56 learner (0.49)
The recommended learner with third priority	Number 40 learner (0.72)	Number 56 learner (0.45)	Number 58 learner (0.265)

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