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Using a genetic algorithm to determine optimal complementary learning clusters for ESL in Taiwan

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A R T I C L E I N F O

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A B S T R A C T

This paper proposes a strategy for using students' complementary competencies in cooperative learning to increase their English learning performance. The concept of complementary learning is based on the idea that teaching is learning. The foundation of the complementary learning concept is composed of three stages proposed to derive the optimal learning clusters—input stage, genetic algorithm (GA) stage, and output stage. In tests and verification of the feasibility of using optimal complementary learning clusters in increasing students' English learning outcome, comparisons between the experimental group (the optimal complementary learning clusters) and the control group showed that students in the experimental group had higher performances in listening, speaking, and reading competencies than those in the control group. Finally, according to the respective importance weights of different English competencies in different learning objectives, the fuzzy linguistic terms were applied to derive optimal complementary learning clusters to maximize students' learning outcome.

1. Introduction

Cluster learning is a form of cooperative learning. The benefit of cluster learning is that students can acquire, share, and coordinate knowledge through a cooperative process. McConnell's research (1996) demonstrates that active and cluster learning methods increase students' knowledge and learning outcomes in the classroom. Besides, cluster learning brings the additional benefit of preparing students to be accustomed to future professional environments. Nichols and Miller's research (1994) reveals that students in a cooperative classroom exhibit significantly greater gains in achievement, efficacy, intrinsic values, and learning goal orientation than those in traditional lecture clusters. Kirschner, Beers, Boshuizen, and Gijselaers (2008) conducted a series of experiments on cluster learning, showing that a tool capable of facilitating negotiation between individual standpoints can bring positive effects by achieving common ground. However, according to Wong (2004), tension and disadvantage may arise when managing two types of cluster learning simultaneously, because a higher level of group cohesion may increase distal learning but in some ways decrease local learning. In other words, when students engage in both local learning and distal learning, distal learning may inhibit local learning from accomplishing a higher level of group efficiency.

Language-learning activities incorporate cluster learning primarily in conversation exercises. Oxford and Ehrman (1995) explored adult language learning strategies in intensive foreign language programs. They examined how an individual's language learning strategies correlate with their language competency and with diverse cognitive, affective, and social factors. Optimal learning groups are created taking into consideration the students' language competency and individual characteristics. Ghaith and Yaghi (1998) compared the effect of cooperative learning on English language acquisition with the individualistic instructional approach mainly based on textbook exercises. The research results show that low achievers in the experimental groups make more gains than their high-achieving counterparts in the same groups, without inhibiting their high-achieving group mates. Wood and Head (2004) applied a problem-based leaning to biomedical English instruction, which is a problem-oriented, cluster-based, and student-centered approach.

Hinger (2006) revealed that group cohesion is a powerful indicator of group motivation, and an intensive course can create a supportive classroom environment that enhances group cohesion. An appropriate distribution of instructional time may also enhance group cohesion and group learning. Yang and Chen (2007) investigated the effect of the integration of multimedia technology in six English teaching activities—cluster e-mailing, a Web-based course,

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an e-mail writing program, English homepage design, video-conferencing, and chat room discussion. Their study shows that students with different learning backgrounds can enhance each other's educational experiences by bringing different perspectives to English language learning. Krecic and Grmek (2008) explored grammar and elementary school teachers' perceptions of cooperative learning to assess the value of cluster learning in comparison to individual learning. Their results show that cluster learning enables participants to compare their opinions with those of others, yielding deeper insight.

In summary, the above literature review indicates that cluster learning can enhance participants' learning outcome and communication. However, participants in the above-mentioned groups are clustered mainly based on their similar characteristics, rather than their complementary characteristics. This paper takes students' complementary competencies into consideration while clustering students for a course of English as a Second Language (ESL). For example, the student who has better English-speaking competency is clustered with the student who has better English writing competence but worse speaking competence and the student who has better reading competence but worse speaking competence. Hence, these students with distinct English competencies and skills are clustered into the same group to teach and learn from each other, exchanging their learning methods and experiences in English speaking, reading, and writing. The concept of complementary learning is based on the idea that teaching is learning. When someone else is teaching, students are taught what they do not know; by teaching, they become aware of the shortcomings in their own knowledge. Based on the concept of complementary learning, this paper proposes three stages to derive the optimal cluster for complementary learning: input stage, genetic algorithm (GA) stage, and output stage. The input stage served to collect students' initial English scores and normalize the data of their scores. The GA stage used a genetic algorithm to derive the result for the output stage. The output stage focused on finding the optimal clusters for implementing complementary learning. Section 2 contains a detailed description of the three stages for obtaining the optimal complementary learning clusters. Section 3 presents the empirical experiment for verifying the performance of complementary learning clusters. Section 4 uses fuzzy linguistic rules to derive complementary learning cluster to maximize students' learning outcome according to the respective importance weights of different English competencies in different learning objectives. Section 5 gives the conclusion of this paper.

2. Three stages to obtain the optimal clusters for complementary learning

In this research, three stages—input stage, GA procedure, and output stage—were developed to obtain the optimal clusters for complementary learning. The following Fig. 1 is a detailed description of the three stages.

2.1. Stage I. Input

The input stage included the following two steps. Step 1 was to collect the students' initial English scores and Step 2 was to normalize the data of the students' initial English scores.

2.1.1. Step 1. Collecting students' initial English scores

Forty-five students at a university in central Taiwan were selected as the experimental sample. To assess the students' initial English levels, it was necessary to collect their initial English scores. The students' English scores of the previous semester—in listening, speaking, and reading—served as their initial English scores, and distinguished the English proficiencies between students in these three competencies to further derive optimal clusters for implementing complementary learning.

2.1.2. Step 2. Normalizing the data of students' initial English scores

This step normalizes students' initial English scores to avoid the various effects of adopting different standards for measuring students' distinctive and distinguished English proficiencies. The following Eq. (1), Z_{ij} ($0 \leqslant Z_{ij} \leqslant 1$), was the method of normalization.

$$Z_{ji} = \frac{X_{ij}}{X_j^{\max}}, \tag{1}$$

where

$$X_j^{\max} = \max\{X_{ij},\ i = 1, 2, \ldots, 45\}, \quad j = 1 \text{ for listening}, 2 \text{ for speaking}, 3 \text{ for reading} \tag{2}$$

and

$$X_j^{\min} = \min\{X_{ij},\ i = 1, 2, \ldots, 45\}. \tag{3}$$

The notation is described as follows:

Z_{ij} is the ith student in the jth normalization score in English proficiency.
X_{ij} is the ith student in the jth initial score in English proficiency.
$X_j^{\max}$ represents the maximal scores in the jth initial score in English proficiency.
$X_j^{\min}$ represents the minimal scores in the jth initial score in English proficiency.

Table 1 shows the normalization scores for 45 students in different English proficiency sections.

2.2. Stage II. GA procedure

2.2.1. GA procedure

GA is a search technique used to find optimal solutions to problems, based on the Darwinian principle of "survival of the fittest" and genetics in biological systems (Goldberg, 1989). The optimal solution is derived after going through a series of iterative computations to deal with large search spaces randomly and efficiently to obtain near optimal solutions to complex problems (Fogel, 1994). The GA generates a series of alternate solutions, which are represented by a chromosome. The series of alternate solutions serve as solution options to the problem until acceptable results are obtained. A GA can quickly derive an optimal solution without examining all possible solutions to the problem. To obtain an optimal solution, a typical GA uses three main operators—selection, crossover, and mutation—to improve the fitness of a population of guesses toward convergence (Goldberg, 1989).

Based on the above GA methodology, in this paper, the GA was performed to obtain the optimal clusters for complementary learning. The tests utilized the Evolver 4.0 software for Excel as the solving tool. Order-based GA was adopted as the solving method to determine the optimal complementary learning clusters. The solving method of order-based GAs provides a permutation of a list of items, deriving the optimal order from a list of items, which is called order crossover (Davis, 1985, 1991). Order crossover is regarded as one of the best solving methods in terms of quality and speed (Larranaga, Kuijpers, Murga, Inza, & Dizdarevic, 1999).

According to Davies (1991), order crossover creates an offspring by the following procedure.

Input: two parents.
Output: a child.
Step 1: Select a substring from parent 1.