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# Personalized e-course composition approach using Digital Pheromones in improved particle swarm optimization

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***Abstract*—One of the uphill tasks associated with the authoring of e-courses, for e-learning systems, is that the current composition techniques do not support 'personalized-learning' or in other words, the current composition methods fail to take into consideration the difference in individual learning capabilities and the background knowledge of the individual learners, which do not provide materials that exactly meet the demands of the individual learners. In order to provide solution for this problem, in the past, various e-course composition approaches had been proposed to use various methods of computational optimization techniques like genetic algorithm and particle swarm optimization. This paper proposes an improved personalized e-course composition approach based on modified particle swarm optimization algorithm along with digital pheromones. The final results of our ongoing research in this area, is furnished in this paper. Results of the various simulation-based experiments that have been conducted are furnished at the end of this paper. These results demonstrate that our proposed approach is an effective solution to the problem of 'personalized learning'. In addition, our proposed approach is compared with the existing approaches, which uses Basic particle swarm optimization algorithm (BPSO) and modified PSO algorithm. These comparisons demonstrate that our proposed model is more efficient than others.**

***Index Terms*—E-learning, Personalized e-course composition, personalized learning, Particle swarm optimization(PSO), digital pheromones, efficient swarm coordination, adaptive e-learning**

## I. Introduction

Learning via computing devices, aided by technological innovations like internet, is known as e-learning or web-based learning [1]. An ideal e-learning system provides an online learning environment whose primary functionalities are to (1) deliver e-learning materials, (2) record learning experience and (3) manage e-learning materials and e-courses [2]. Many standards such as Content Aggregation Model (CAM) of Sharable Content Object Reference Model (SCORM) [2] have been instituted with the aim of reusing the available e-learning materials. Also some e-course authoring tools have been developed to facilitate instructors in e-course editing [3], [4], [5]. However all the afore-mentioned composition approaches fail to take into consideration the difference in individual learning capabilities and the background knowledge of the learner while composing the e-courses. As a result the composed courses do not support the individual learner's demands or in other words, the existing composition approaches do not suppport 'personalized learning'. Providing materials that meets demands of individual learners is defined as 'personalized-learning' [3], [4], [5]. This paper is an effort to trace this definition. In the past, various approaches have been proposed to provide solution to the above mentioned problem of 'personalized learning' [1], [2], [3], [4], [5]. In 2009, Chu et al proposed a 'personalized e-course composition approach, based on basic particle swarm optimization algorithm (BPSO) [6]. This 'personalized e-course composition approach' was modified by Dheeban et al using a modified particle swarm optimization algorithm (MPSO) [7] with inertia coefficient [8], [9], [10] to improve the solution characteristics. In this paper we propose to modify the MPSO algorithm using digital pheromones [11] which drastically improves the solution characteristics.

## II. Problem Background

Certain factors have been identified as the important contributing parameters that need to be considered, to effectively solve the problem of 'personalized e-learning' in [6]. They are as follows:

1) Whether or not the covered learning concepts of the personalized e-course meet the expected learning target of a learner: The expected learning target of a learner depends on his/her past learning experience.
2) Whether or not the difficulty of the e-learning materials matches a learner's ability: The ability of a learner depends on age, the level of education and learning subjects, and so on.
3) The limitation of learning time for individuals: since a learner's ability and attention affect individual learning time, the expected learning time for each learner is different.
4) The weight of learning concepts covered in a personalized e-course: To avoid the situation that the weight of covered learning concepts in a personalized e-course is not balance, the balance of the weight of learning concepts needs to be considered.

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All the afore-mentioned factors have been represented as fitness functions in [6], which facilitate the usage of evolutionary algorithm like particle swarm optimization (PSO) for this specific problem statement[12], [13]. In addition, they have identified five parameters that vividly describe the individual learner and five other parameters that describe the characteristics of the learning materials that are a part of the e-course to be offered. They are as follows

### A. Definition of Parameters

1) Parameters regarding learners
   a) $\{L_1, L_2, ..., L_k\}$ denotes K learners.
   b) $\{A_1, A_2, ..., A_k\}$ denotes the ability level of K learners where $A_k$, 1≤k≤K, denotes the ability level of learner $L_k$
   c) $\{H_1, H_2, ..., H_k\}$ denotes the expected learning targets of K learners where each $H_k$ has M binary values, $H_k$=$\{h_{k1}, h_{k2}, ..., h_{km}\}$, where $h_{km}$=1, if 1≤k≤K and 1≤m≤M, represents the expected learning target covers the learning concept $C_m$. Else it is 0.
   d) constraint $t_{l_k}$ , 1≤k≤K : Lower bound on the expected learning time of an e-course for the learner $L_k$.
   e) constraint $t_{u_k}$ , 1≤k≤K : Upper bound on the expected learning time of an e-course for the learner $L_k$.
2) Parameters regarding e-learning materials
   a) $\{C_1, C_2, ..., C_M\}$ denotes M learning concepts which the learner expects to learn from an e-course. These relate to the specific concepts in a curriculum.
   b) $\{LM_1, LM_2, ..., LM_N\}$ denotes the N candidate e-learning materials each of which covers different concepts.
   c) $\{D_1, D_2, ..., D_N\}$ denotes the difficulty level of the N candidate e-learning materials where $D_n$ , 1≤n≤N, denotes the difficulty level of e-learning material $LM_N$.
   d) $\{R_1, R_2, ..., R_N\}$ denotes the covered learning concepts of N e-learning materials where each $R_n$ has M binary values i.e $R_n$ = $\{r_{n1}, r_{n2}, ..., r_{nm}\}$ and $r_{nm}$=1, 1≤m≤M, if the e-learning material $LM_n$ covers the concept $C_m$ and $r_{nm}$=0 otherwise.
   e) Coefficient $t_n$, 1≤n≤N: Required time for reading the e-learning material $LM_n$.
3) Decision variable $X_{nk}$, 1≤n≤N and 1≤k≤K: where $X_{nk}$=1 if the e-learning material $LM_n$ is to be composed into the e-course of the learner $L_k$, and $X_{nk}$=0 otherwise.

### B. Definition of fitness-function

Chu et al further represented the four criteria mentioned earlier as four sub-fitness functions [6] as follows:

1) Sub-fitness function, $F_1$, gives the average difference between the covered learning concept and the expected learning of a learner $L_k$. This objective function gives an idea about which learning materials cover the learning concepts needed by the learner.

$$F_1 = \frac{\sum_{m=1}^{M}\sum_{n=1}^{N} X_{nk}|r_{nm}-h_{km}|}{\sum_{n=1}^{N} X_{nk}},\ 1\leq k\leq K$$

2) Sub-fitness function, $F_2$, gives the average difference between the difficulty level of the e-learning material and the learner's ability level. This objective function helps in identifying e-learning materials which suits the ability level of the learner $L_k$.

$$F_2 = \frac{\sum_{n=1}^{N} X_{nk}|D_n - A_k|}{\sum_{n=1}^{N} X_{nk}},\ 1\leq k\leq K$$

3) Sub-fitness function, $F_3$, gives the required learning time between the lower and upper bound of the expected learning time of the learner $L_k$. This objective function is to ensure that the total time required for finishing the e-learning materials which are selected for the particular learner, fall within that learner's expected learning time.

$$F_3 = \left(max\left(t_{l_k} - \sum_{n=1}^{N} t_n X_{nk}, 0\right)\right) + \left(max\left(0, \sum_{n=1}^{N} t_n X_{nk} - t_{u_k}\right)\right)$$

4) Sub-fitness function, $F_4$, is used to balance the weight of the learning concepts. This is used in order to avoid the situation where the learning concepts covered in a personalized e-course are not in balance.

$$F_4 = \sum_{m=1}^{M} h_{km}\left|\sum_{n=1}^{N} X_{nk} r_{nm} - \frac{\sum_{n=1}^{N}\sum_{m=1}^{M} X_{nk} r_{nm}}{\sum_{m=1}^{M} h_{km}}\right|\ 1\leq k\leq K$$

The afore-mentioned four sub-fitness functions are aggregated after being multiplied by their corresponding relative weights (w1,w2,w3,w4) in order to obtain the final fitness function, F.

$$\min F(x) = \sum_{j=1}^{4} w_j F_j$$

The basic idea is to minimize each of the sub-fitness functions, which is achieved when the final fitness function is minimized.

## III. METHODOLOGY

This section discusses the methodology we propose to incorporate in our approach, in order to provide an effective solution to the problem statement defined in the previous section. We proposed to use an improved particle swarm optimization (PSO) algorithm with digital pheromones to improve the solution characteristics for personalized e-course composition [11].

### A. Digital Pheromones

Pheromones are chemical scents produced by insects essentially as a means of communication in finding suitable food and nesting locations. The more insects travel a path, the stronger the pheromone trail. A digital pheromone, which has been inspired by this concept, is used to explore search space and leave a marker in potential regions where future investigation would be useful. This would aid in speeding up the process of searching for optimum solution.

### B. PSO and digital pheromones

Kalivarapu et al. in [11] found that the benifits of digital pheromones from swarm intelligence and the adaptive applications described above can be merged into PSO to improve design space exploration. By doing so it was observed that the solution characterstics of the basic PSO algorithm could be drastically improved.

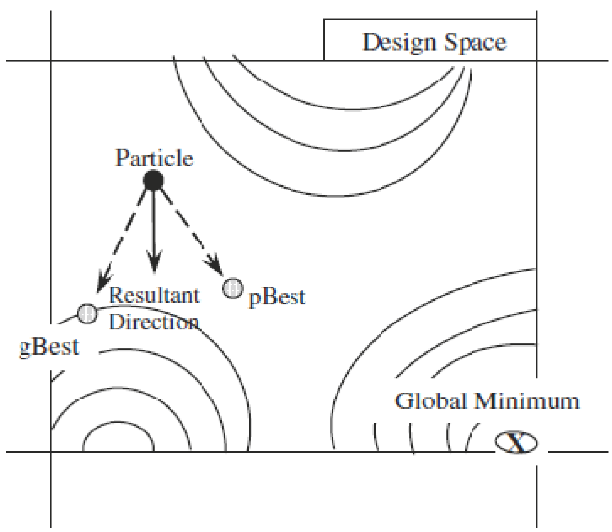


Fig. 1. Particle movement within a basic PSO

In a basic PSO algorithm, the swarm movement is governed by the velocity vector. Each swarm member uses information from its prevoius best (pBest) and the best member in the entire swarm at any iteration (gBest). However [11] observes that the presence of pheromones in the design space would improve the solution characteristics by providing more information about the design space. This would be more useful when the information provided by pBest and gBest are insufficient. Figure 1 (from [11]) displays a scenario of a swarm member's movement whose direction is guided by pBest and gBest alone. If $C_1 >> C_2$, the particle is strongly attracted to the pBest position. On the other hand if $C_2 >> C_1$, the particle is strongly attracted to the gBest position. In the scenario dominated by $c_2$, as presented in Fig.1 neither pBest nor gBest leads the swarm member to the global optimum, at the very least, not in this iteration adding additional computation to find the optimum.

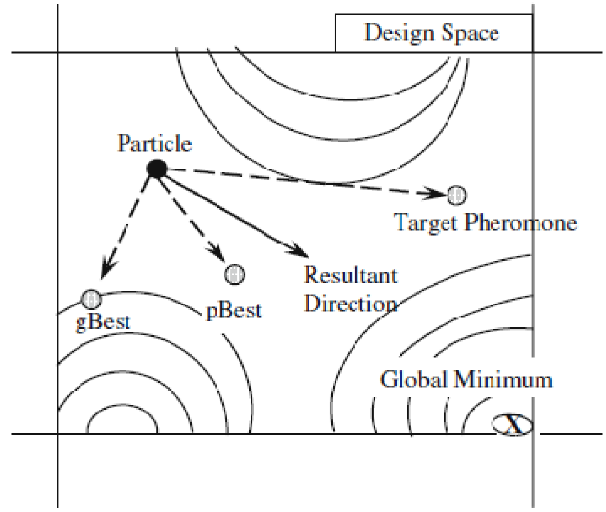


Fig. 2. Particle movement with digital pheromones

Figure 2(from [11]) shows the effect of implementing digital pheromones into the velocity vector. In this implementation an additional velocity component is being added to the velocity vector. An additional pheromone component potentially causes the swarm member to result in a direction different from the combined influence of pBest and gBest, thereby increasing the probability of finding the global optimum, as observed by [11].

### C. Digital pheromone implementation

Kalivarapu et al implemented the digital pheromones into the basic PSO algorithm [11]. In this implementation the swarm is initialized like the Basic PSO but 50 percent of the particles are selected randomly and made to release pheromones for the initial run alone. During the future runs only those swarm members which experienced an improvement in their objective function where made to release the pheromones. Pheromones from the current as well as past iterations that are close to each other in terms of the design variable value can be merged into a new pheromone location, in order to manage the number of pheromones in the design space. In addition, the digital pheromones are decayed in every iteration just as natural pheromones. Based on the current pheromone level and its position relative to a particle, a ranking process is used to select a target pheromone for each particle in swarm. This target position toward which a particle will be attracted is added as an additional velocity vector component to pBest and gBest. This procedure is continued until a prescribed convergence criterion is satisfied. Figure 3 provides steps required to implement the above mentioned steps, which is furnished from [11]

### D. Determination of target pheromone

Kalivarapu et al [11] found the need to identify a target pheromone for each of the particle owing to the fact a large number of pheromones was generated. In [11] they established a criterion that is a function of (a) the distance between the

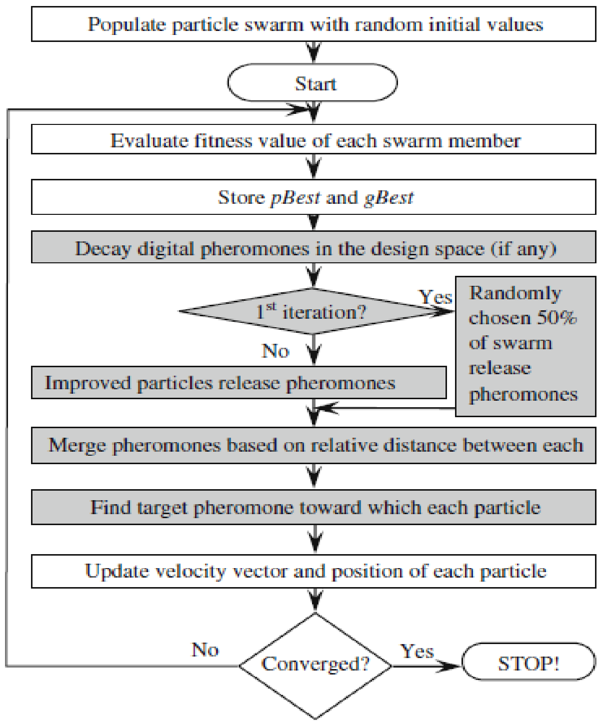


Fig. 3. Flowchart of PSO with digital pheromones

particle and the pheromone and (b) the pheromone level. For each particle, a target pheromone attraction factor P' is computed to this effect, which is a product of the pheromone level and the normalized distance between the particle and the pheromone. Equation (1) shows how the attraction factor P' is computed, and (2) computes the distance between the pheromone and each particle in the swarm as guided by [11]

$$P' = (1\text{-}d)\ P \qquad \text{-(1)}$$

$$d = \sqrt{\sum_{l}^{k}\left(\frac{X_{pk}-X_k}{range_k}\right)^2} \qquad \text{-(2)}$$

Where k=1:n, No. of design variables, $X_p$=location of pheromone, X=location of particle

### *E. Velocity vector update*

The velocity vector update, shown in (3), implements digital pheromones described above as guided by [14]. This involves a new component called the Target Pheromone in the equation for velocity update.

$$\begin{aligned} V_{i,d}^{t} &= \omega * V_{i,d}^{t-1} + C_1 * Rand_1 * (pbest_{i,d} - Y_{i,d}^{t-1}) \\ &+ C_2 * Rand_2 * (gbest_{i,d} - Y_{i,d}^{t-1}) \\ &+ C_3 * Rand_3 * (Targetpheromone_{i,d} - Y_{i,d}^{t-1}) \text{ -(3)} \end{aligned}$$

Kalivarapu et al in [11] observed that, $C_3$ is a user defined confidence parameter that combines the knowledge from the cognitive and social components of the velocity of a particle and complements their deficiencies. In a basic PSO, there is no memory of the path traversed by the swarm. According to [11] the target pheromone component was found to address this issue. The target pheromone was found to steer the swarm towards the optimum solution by keeping track of the path visited by the particles. The additional pheromone term in the velocity vector update can considerably increase the computed velocity. Therefore, a move limit was applied to impose an upper bound on maximum value of the velocity vector. To ensure a fair amount of freedom in exploring the design space, the swarm is allowed to digress up to 10 percent of the range of the design variables initially. A decay factor of 0.95 is applied to this move limit in subsequent iteration as guided by [11] which decreases the freedom to explore the design space as the iteration progress forward.

## IV. EXPERIMENTS AND RESULTS

A variety of simulation based experiments were conducted, in order to evaluate the approach proposed in the previous section. A vivid account of all the experiments performed to verify our proposed approach are furnished in this section. The section is concluded with the results of the various experiments that show the effectiveness of our proposed approach.

### *A. Experiments*

We simulated the algorithm (IPSO) mentioned in the previous section and compared it with three other algorithms which were implemented for the same problem statement namely BPSO[6], LPSO and RPSO[7].
Experiments were conducted under the following environment: Windows Vista home premium service pack 1, CPU: Intel(R) Core(TM) 2, RAM: 4 Giga Byte, Programming language used : C-language, compiled and run in Microsoft visual C++ 6.0

*1) Experiment 1:* The aim of this experiment is to obtain the fitness value from the IPSO algorithm and compare it with that obtained from BPSO, LPSO and RPSO [6], [7] for this problem statement. In order to acheive that all the four algorithms were run with identical values as guided by [6], set for the parameters regarding e-learning materials. The values of $C_1$ and $C_2$ were set as 2.0 as informed by [12],[13] for the first three models of PSO and value of $C_3$ was set as 2.0 as informed [11] for IPSO. The number of particles was set to 20. For all the four models, the velocity of the particles were restricted in the range of [0,1] as suggested by [13].The iteration maximum was set as 1000. The termination criterion (TC) was set uniformly as 1000 iterations for all the algorithms. Fig 4 shows the graph obtained from this experiment.

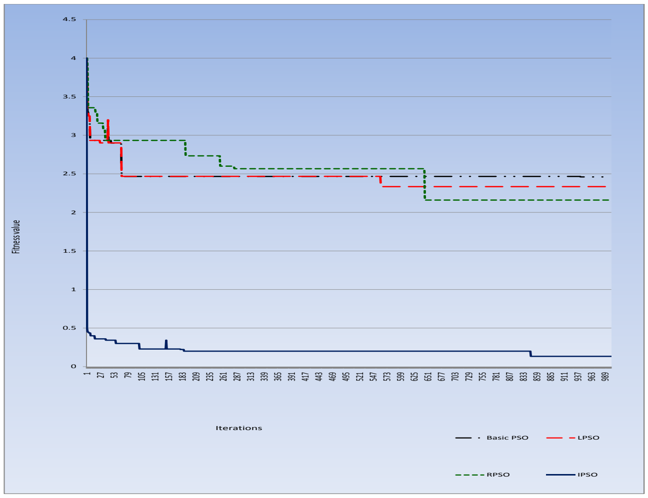


Fig. 4. Comparison of fitness values obtained from BPSO, LPSO, RPSO and IPSO

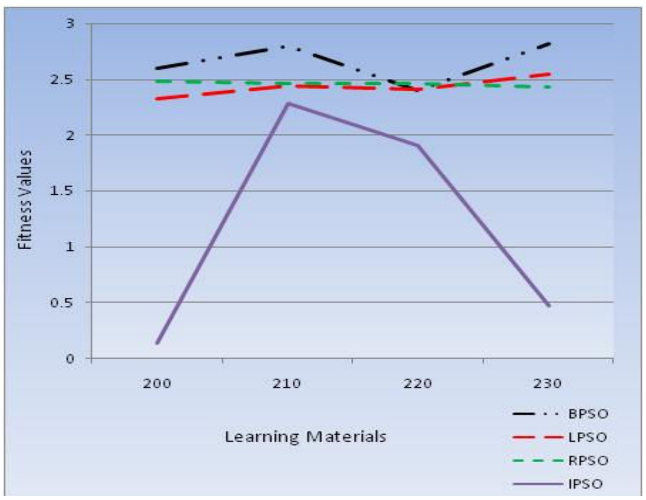


Fig. 5. Effect of varying number of learning materials

*2) Experiment 2:* The aim of this experiment is to compare our proposed tecnique to construct the e-learning course with that of the other models which use PSO [6], [7] when the number of learning materials is increased. Here all the values of the previous experiment was kept constant except for the number of learning materials which was changed. The result from this experiment is shown in Fig 5.

### *B. Results*

The graph obtained from above mentioned experiments are furnished in this section. The first garph gives the comparative performance of the existing BPSO, LPSO and RPSO with our proposed technique(IPSO). The second graph illustrates the variation of fitness values for all the four models when the number of learning materials is varied.

### *C. Description*

From fig 4, we can observe that when all the four models are evaluated under the same experimental conditions, for the same number of learning materials, the quality of final fitness values provided by our proposed variant of IPSO along with digital pheromones is superior when compared to the currently existing PSO approaches i.e.the e-course composed using our approach best suits the learner and offers a more personalized e-learning material than the ones offered by other existing techniques.
The result of the second experiment which is depicted in Fig.5 clearly depicts that our proposed techniques outperforms the existing techniques providing an optimimum solution even as the number of e-learning materials increase. This would mean that our model would give out an optimum and better solution in all possible cases.

## V. CONCLUSION

In this paper, we have proposed an improved personalized e-course composition approach using improved particles swarm optimization(IPSO) algorithm. The experimental results indicate our proposed IPSO approach provides better solution-quality than the existing approaches. Under the identical conditions our proposed algorithm outperforms the existing PSO approaches, when the learning material count becomes large.

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