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# Using Particle Swarm Optimization Approach for Student Engagement Measurement

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**Abstract.** Measuring Student Engagement is a difficult task. Previous research has used a cloud-based writing platform, Google Docs, which can store a number of document revisions with timestamps. Engagement measurement algorithm has taken the advantages of each timestamp in a revision and calculated how much time the student spent on a writing task. However, the parameters passed to the algorithm were fixed and hard to determine, for example, how much time means fully engaged or partially engaged. In this paper, we proposed a new student engagement measurement algorithm based on a computational intelligence approach, Particle Swarm Optimization technique, to find the optimized parameters for the engagement measurement algorithm. In the study, the proposed algorithm measures the engagement of two groups of students in two different writing activities (long-term and short term writing activities) carried out in our cloud-based writing platform. The study results show that the correlations between the engagement measurement and student self-report are high. In addition, it indicates that this approach is robust to measure student engagement in both long-term and short term activities.

**Keywords:** Student Engagement Measurement, Advanced Educational Technologies, Particle Swarm Optimization.

## Introduction

Student engagement plays an important role in a learning activity. Studies (Fredricks, Blumenfeld, & Paris, 2004) show that a student who is engaged and intrinsically motivated in a task is more likely to learn from an activity and models of school engagement identify three core dimensions: behavioral, cognitive and emotional engagement. 'Behavioral engagement', which is the focus of the present study, refers to student participation in school related activities and involvement in any learning tasks such as those being done online (Fredricks et al., 2004). 'Cognitive engagement' refers to motivation, thoughtfulness and willingness to make an effort to comprehend ideas and master new skills. 'Emotional engagement' includes emotions and interest, such as affective reactions in the classroom towards teachers. These three aspects are interrelated and helpful to understand engagement as a whole.

The measurement of behavioral engagement is more obvious because behavioral patterns can be defined, observed and interpreted. Traditionally, student engagement is measured by teachers' observation (Bulger, Mayer, Almeroth, & Blau, 2008; Martin, 2007). But, this approach is time consuming and subjective. In the era of 'big' data, a large amount of student data about their behavior being harnessed to improve learning interactions and to personalize the learning experience can be collected by the system (Tanes, Arnold, Selzer King, & Remnet, 2011). For instance, when a student participates in an activity that is technology mediated, a detailed collection of behavioral events can be recorded. Computer keystroke-logging (Leijten & Van Waes, 2013) or screen capturing (Latif, 2008) allow a detailed account of the behavior of a writer including actions such as starting a new paragraph or deleting a text portion and these are all considered indicators of behavioral engagement. Thus, new computer technology permits the observation and identification of learning events, which can then be examined in relation to other indices of engagement. However, these technologies require specialized setups and often hardware.

In the recent year, with the development of the cloud-based online writing platform, such as Google Doc or Wiki, it is possible to capture student's writing behavior easily by utilizing document revision history (Cole, 2009; Liu et al., 2013). However, the engagement measurement algorithm requires so many predefined parameters, such as the time threshold for full engagement or for partial engagement. Previously, the thresholds are determined by educational experts, which is too subjective. If the thresholds are set too high or too low, it would affect the accuracy of engagement measurement and effect of engagement visualization.

Particle swarm optimization (PSO) is a population-based metaheuristics used for stimulating social behaviour such as fish school to a promising position (S. W. Lin, Ying, Chen, & Lee, 2008). PSO is a subset of swarm intelligence which was occurred in the late 1980s to relate to cellular robotic systems, where a number of agents in an environment interact based on local rules. Over the past years, particle swarm optimization technique has lately been illustrated to have the ability to solve complex problems, such as automatic group composition(Y.-T. Lin, Huang, & Cheng, 2010), e-learning problems(Huang, Huang, & Cheng, 2008), automatic test sheets generation (Yin, Chang, Hwang, Hwang, & Chan, 2006). These studies suggested that swarm intelligence is useful for providing high scalability and robust computation. In our study, we use PSO to optimize the engagement measurement algorithm.

## Behavioural Engagement

Studies of behavioural engagement in learning environments typically use evidence collected by human observers, such as teachers or students (Lane, 2009; Martin, 2007). For example, using scales such as the Student Engagement

Walkthrough Checklist, observers such as administrators, instructional supervisors or teachers, have examined the degree to which students exhibit engagement in the classroom, by measuring behaviors such as positive body language, consistency of focus, spoken participation (Jones, 2009). The observer ratings are then compared to simultaneous and anonymous ratings by students of their level of engagement according to the extent to which the work is interesting and challenging, and the degree to which they understand why and what they are learning.

Jones (2009) have defined the models of general engagement including behavioral, emotional and cognitive engagement as consisting of three dimensions; intensity, consistency and breadth. Intensity relates to the level of engagement of each student. Consistency refers to how long students remain engaged at high levels throughout the class period and breadth refers to how broadly the class as a whole is engaged. Measuring dimensions of engagement allows teachers to provide differentiated feedback. For example, if the engagement intensity is low, teachers can focus on adding rigor and relevance to expectations and lessons.

To date, most of the research on student engagement has occurred in classrooms (Sheldon & Biddle, 1998), yet researchers are increasingly exploring learning theories in web-based activities (Chena, Lambertb, & Guidryb, 2010), social software (2009), smart interactive devices (Blasco-Arcas, Buil, Hernández-Ortega, & Sese, 2013) and virtual environments (Bouta, Retalis, & Paraskeva, 2012). 'Clickers' (Blasco-Arcas et al., 2013) allowed students to quickly answer questions presented in class. Responses can be anonymized or identified and software programs are usually used to summarize responses and present visualizations in the form of charts. Technology-based tools such as Wiki technology (2009) have been used to support learning engagement. Cole (2009) tested Wikis in a third year undergraduate course to examine the degree to which they supported student knowledge construction, peer interaction and group work. However given the optional nature of this form of technology in the course, students did not contribute to the Wiki as was intended. Thus focus groups were used to examine barriers to uptake rather than the effects of Wikis on student engagement per se. However, a limitation of previous studies is that they have not addressed how to automatically track and analyze student behaviour patterns and present them in a way that is understandable. Given the difficulties identified by previous studies (2009) related to student use of web-based techniques the present study was conducted within a laboratory environment rather than as part of a course.

## Engagement Visualization and Measurement

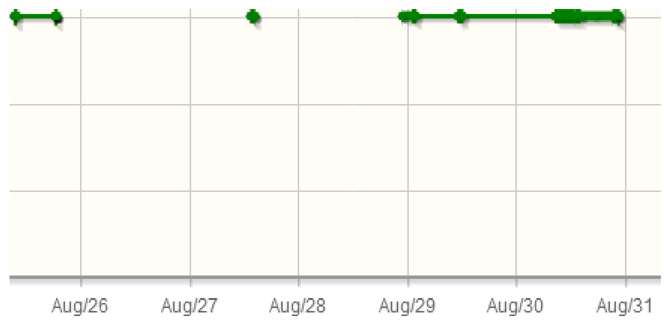


**Figure 1: Line-based Visualization: green lines with different thickness show that a user has done several intensive writing in the drafting process. Graphs are copied from (Liu, Calvo, & Pardo, 2013).**

Engagement is critical to the success of learning activities such as writing, and can be promoted with appropriate feedback. Tracer is a learning analytic system (Liu et al., 2013) which derives behavioral engagement measures and creates visualizations of behavioral patterns of students writing on a cloud-based application. Figure 1 shows that the Line-based Visualization uses a line to connect the points and the thickness of a line indicates the intensity of the user's behavior during a period of time. This information is derived from Intensity-based engagement measurement algorithm (IbA), where a series represents a line and its weight represents a line thickness. Therefore, the whole graph is made of lines. The weighting process is defined as follows:

1. A hashmap is predefined, where each entry contains a time threshold and a corresponding weight value. For example, (0.5h, 0.8) indicates that the time threshold is 0.5h and its corresponding weight is 0.8.
2. If the duration between neighboring events is less than the shortest time threshold, we assign that corresponding weight to the series. For example, in one month project proposal writing assignment, the following combinations/hashmap: (0.5h, 1), (1h, 0.8), (3h, 0.4) and (12h, 0.2) is considered based empirical experience. For example, if the duration of an activity is 2 hours, we assigned 0.4 as a weight to the series because 3h is the shortest time defined in the hashmap that is longer than 2h.

Thus the total engagement score is calculated as the following weighted sum:

$$\text{Engagement}=\sum_{i}^{n} s_i * w_i \qquad (1)$$

where i is the index of a series, $S_i$ is the duration of the series i and $W_i$ is the weight assigned to i.

## Particle Swarm Optimization

PSO looks through a collection of individual solutions called particles that update iteratively. Each particle at iteration t can be represented by a D-dimensional state vector as $x_i^t = \{x_{i1}^t, x_{i2}^t, \ldots, x_{iD}^t\}$. Then, to obtain the optimal solution, we define D-dimensional velocity vectors $V_i^t = \{V_{i1}^t, V_{i2}^t, \ldots, V_{iD}^t\}$ for each particle and determined by its own best previous experience, denoted as pbest, and the best experience of all the particles, denoted as gbest. Particles change velocity based on the pbest and gbest as follows:

$$V_{id}^t = V_{id}^{t-1} + c_1 r_1 \left( pbest_{id}^t - X_{id}^t \right) + c_2 r_2 \left( gbest_{id}^t - X_{id}^t \right)$$

$$,d=1,2,3\ldots D \qquad (2)$$

Where $c_1$ *and* $c_2$ are the learning factors which are commonly set to 2 and $r_1, r_2$ are random numbers distributed uniformly in the range [0, 1]. Then, each particle updates to a new potential answer based on the velocity as:

$$X_{id}^{t+1} = X_{id}^t + V_{id}^t \qquad (3)$$

When the iteration number reaches a pre-determined maximum iteration number, the update process is terminated and the best individual of the last generation is the final solution to the target problem.

## PSO enhanced Engagement Measurement Algorithm

In this section, we describe the proposed PSO-EM algorithm for predicting the total time a student spent on the writing task. The aim of this study is to optimize the accuracy of the engagement prediction by estimating the best values of an engagement measurement function parameters described above. We used the Matlab to implement this algorithm. The evaluation matrix for SVR is MSE (mean square error).

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(f(x_i) - y_i)^2 \qquad (4)$$

MSE is a common evaluation measurement for numeric value prediction, which has been adapted in education (Tang & Yin, 2012).

In our study, PSO starts with 20-randomly chosen particles and looks for the best particle iteratively. Each particle is a 6-dimensional vector including three time thresholds and three weights represents a candidate solution. The engagement measurement algorithm is constructed for each candidate solution to estimate its performance. The procedure describing proposed PSO-SVR approach is as follows.

*Function PSO-EM () {*

*Initializing PSO with 20 particles and each engagement measurement algorithm with each particle.*

*Evaluating the fitness (MSE) of each particle.*

*For each iteration in 200*

*For each particle in 20*

*Calculating the particle velocity and updating the particle*

*Calculating the fitness of the particle by passing the parameters to engagementMeasurement()*

*Comparing the fitness values and updating the local best and global best particle.*

*End*

*End .*

*}*

## Study

In order to evaluate the feasibility of the proposed engagement measurement algorithm, we have conducted a study, where 120 students were writing an individual document in a web-based writing system. This system is developed based on etherpad (http://etherpad.org/), which is an online real-time text editor, letting authors to write a text document, and look all the revision history of the document. Each document revision history has been recorded in a textual database. We need to extract the timestamp of each revision as an input to the engagement algorithm.

### Participants and Procedure

A total of 120 university students participated in this study. The participants' age ranged from 20 to 30 years (M: 25, SD: 5) and there were 61 males and 59 females. Those student participants came from different disciplines, including computer engineering and education. They had no prior knowledge of the system and did not participated in any previous related study. We arranged a separate one hour writing activity for 60 education majors (writing a personal best travel experience) while one month writing activity (writing a project proposal) for 60 engineering students. We conducted this study in a controlled environment so that each participant could only write in our system (see Figure 2), thus avoiding the 'copy-and-paste' issues. Once the writing activity was finished, each participant was asked to estimate their engagement time in the writing session. The dataset was divided into the training set (n=30) and testing set (n=30) for each activity. We used the training set to train the parameters of the engagement algorithm and testing set to evaluate the performance of the algorithm.


**Figure 2: the user interface in the online writing system**

## Results

The correlation among participants and engagement measurement functions is presented in Table 1. This study results show that correlations between the proposed engagement algorithm (PSO-EM) and human are highly correlated (r=.73 and r=.81) in both writing activities. This algorithm outperformed IbA which has moderate correlation (r=.49 and r=.59) with student self-report (Human). We also observed that the student engagement time in the one-hour writing activity is more predictable than in the one month writing activity, because the one-hour writing activity produced less document revisions.

**Table 1: Correlation of engagement time**

| | One month writing | | | One hour writing | | |
|---|---|---|---|---|---|---|
| | PSO-EM | IbA | Human | PSO-EM | IbA | Human |
| PSO-EM | 1 | | | 1 | | |
| IbA | 0.67 | 1 | | 0.69 | 1 | |
| Human Self-Report | 0.73 | 0.49 | 1 | 0.81 | 0.59 | 1 |

After 200 iterations, PSO-EM converges. Table 2 shows that PSO-EM algorithm (MSE:15.88 in one hour;MSE:31.89 in one month) gets lower MSE scores than traditional IbA (MSE:16.13 in one hour;MSE:64.95 in one month) in both writing tasks (one hour and one month writing tasks).

**Table 2: Performance of PSO-EM Algorithm and Its best parameters. T1 means 1 Time Threshold1 Parameter while W1 means weight1 Parameter**

| **Writing Task** | | **Parameters** | | | | | | **Evaluation Measure** |
|---|---|---|---|---|---|---|---|---|
| | | ***T1*** | ***T2*** | ***T3*** | ***W1*** | ***W2*** | ***W3*** | ***MSE*** |
| One Hour | IbA | 0.5 m | 1.0 m | 2.0 m | 0.33 | 0.66 | 1 | 16.13 |
| | PSO -EM | 3.30m | 4.20 m | 5.12m | 1.09 | 2.34 | 2.89 | 15.88 |
| One Month | ibA | 0.5h | 1.0h | 2.0h | 0.33 | 0.66 | 1 | 64.95 |
| | PSO -EM | 3.3h | 4.20h | 5.12h | 1.09 | 2.34 | 2.89 | 31.89 |

In the one hour writing task, PSO-EM finds the best parameters for this dataset include Threshold1 as 3.30, Threshold2 as 4.20 and Threshold3 as 5.12 minute, and Weight1 as 1.09, Weight2 as 2.34 and Weight 3 as 2.89.

In addition, in the one month writing task, the best parameters for threshold are different from those parameters in one hour writing task and the unit is hour. This result indicates that the PSO-EM algorithm is robust to automatically adjust its parameter values based on the dataset or the nature of the task. It also suggests that PSO-EM outperformed the traditional method.

## Conclusion and Future Work

In this paper, we introduce a novel algorithm, called PSO-EM for engagement measurement, particularly student engagement in a writing activity. This algorithm is based on a computational intelligence approach, called Particle Swarm Intelligence, to find the best parameters for engagement measurement algorithm. Our study result indicates that this algorithm outperformed the traditional engagement measurement method and can automatically adjust the function parameters based on the writing task. We also found that the short-time writing activity (one-week) was more predictable than the long-time writing activity (one-month), since the short-time writing activity produced less revision data for analysis. However, PSO-EM can still perform well in complex revision data due to its robust capability. Our future work will focus on generating real time visualizations based on the engagement algorithm to support individual and collaborative writing.

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