121st ASEE Annual Conference & Exposition
Indianapolis, IN
June 15-18, 2014

Paper ID #10792

Correlating Experience and Performance of On-Campus and On-Line Students Assisted by Computer Courseware: a Case Study

Dr. Hong Man, Stevens Institute of Technology (SES)

Dr. Hong Man joined the faculty of Electrical and Computer Engineering at Stevens in January 2000. He received his Ph.D. degree in Electrical Engineering from the Georgia Institute of Technology in December 1999. Dr. Man is currently an associate professor in the department of ECE. He is serving as the director of the undergraduate Computer Engineering program, and the director of the Visual Information Environment Laboratory at Stevens. His research interests have been in image and video processing, medical imaging, data analysis and pattern recognition. He has authored or co-authored more than 100 technical journal and conference papers on these topics. He is a senior member of IEEE and member of ASEE.

Correlating Experience and Performance of On-Campus and On-Line Students Assisted by Computer Courseware: a Case Study

Abstract

Studies on student surveys can reveal student learning experience, but the results are generally subjective. In this paper, we attempt to correlate students' learning experience with their performance improvement using both survey results and direct assessment results. We use this approach to analyze the effectiveness of learning with the assistance of a computer simulation software, SimuRad, in an undergraduate "Medical Imaging" course. This course is offered regularly in two different modes, i.e. an on-campus section in every Fall semester and an on-line section in every Spring semester. This enables us to compare students' learning experience with the same software in different environment. We use statistical methods to analyze the relationships between four groups of data samples, i.e. on-campus students' survey results, on-campus students' direct assessment results, on-line students' survey results, and on-line students' direct assessment results. Through this study, we are able to verify that there is no deficiency for on-line students to understand course content with the help of the computer lab exercises; and in several scenarios, on-campus students and on-line students behave differently while taking the computer lab exercises. The development and assessment of this software is partially supported by an NSF CCLI grant.

1. Introduction

"Medical Imaging" is an important subject in most bio-medical and bio-engineering curricula[1,2]. To effectively offer this as an introductory undergraduate course, we designed a series of computer lab exercises[3,4] for students to observe the computational and physical processes of medical imaging modalities, and to practice computing skills on bio-medical signal processing. The simulation software suite, SimuRad[5], implements a series of numerical algorithms to simulate the physical and biological processes in several common medical imaging modalities. The software contains expandable modules, each to support a serious lab exercises related to a particular modality. Currently implemented modules include math fundamentals, computed tomography (CT), x-ray physics, nuclear magnetic resonance (NMR), image enhancement and analysis. This assessment study involves six lab exercises, over which both student survey data and direct assessment data were collected for analysis.

Lab 1, Projection and Projection Slice Theorem (tomography)
Lab 2, Frequency domain reconstruction – interpolation methods (x-ray CT, MRI)
Lab 3, Filtered back projection – filtering, noise effects (x-ray CT)
Lab 4, X-ray attenuation coefficient and survival probability (x-ray)
Lab 5, NMR signals – precessions, relaxation, basic sequences (MRI)
Lab 6, Brain activation detection in fMRI (image analysis)

At Stevens Institute of Technology, "Medical Imaging" is a required course in the undergraduate BME program, and it is offered each year in the Fall semester as a regular on-campus course, and in the Spring semester as an on-line course. In the on campus sections, the course constitutes a1.5-hour lecture and a 2-hour lab exercises. In the online sections, students are advised to spend the same amount of time for reading lecture notes and taking lab exercises. Students typically take 9 to 10 weeks to complete all labs, as described in the following sections. Upon completing each lab exercise, students are required to write a lab report. The contents of the lab exercises, e.g. procedures and results, are included in the midterm and final exams. We typically had around 30 students enrolled in the Fall semesters and around 20 students in the Spring semester. The students were from the same student group each year, and mostly of them were our on-campus undergraduate BME students. The reason they took the course in different semester was mostly because of scheduling issues.

The computer lab exercises have been adopted in this course since Fall 2008. During each semester, we conducted a series of assessments through student surveys. By May 2013 we have obtained the survey results for five consecutive years. These results enable us to study student learning experiences in many different ways, which have been reported at previous ASEE Conferences [5,6].

In this study, we focus on correlating students' learning experience with their performance improvement using both survey results and direct assessment results. We use statistical methods[7] to analyze the relationships between four groups of quantitative data samples, i.e. on-campus students' survey results, on-campus students' direct assessment results, on-line students' survey results, and on-line students' direct assessment results.

2. Assessment Methodology

Our assessment of students' learning experience is based on student surveys. We designed a simple set of survey questions for students to complete after each lab exercise. The survey was voluntary. The questions include the scales of student's understand of a certain concept before and after the lab exercise, the scale of knowledge preparation for the lab exercise, the time spent on the lab exercise, and the need for lab design improvement. Following is an example of survey instruction provided in a lab assignment.

> Answer the following survey questions using the scale 1 ~ 5 (1: strongly disagree, 5: strongly agree):
>
> 1. You understand the concept of "filtered back projection method" BEFORE you take this lab exercise. 1 2 3 4 5
> 2. You understand the concept of "filtered back projection method" AFTER you take this lab exercise. 1 2 3 4 5
> 3. You have the knowledge and skill to complete this lab exercise without additional study beyond the lectures. 1 2 3 4 5
> 4. This lab exercise takes you too much time. 1 2 3 4 5
> 5. You think a better lab exercise can be designed to reach the objectives of this lab exercise. 1 2 3 4 5

We have the following considerations in the design of the survey questions:

- The difference between the Q1 score and the Q2 score roughly represents the student's perceived performance improvement.
- The Q4 score, normalized by the Q3 score, roughly indicates the difficulty level of a particular lab.
- The Q5 score indicates the need to improve the usability of the lab.

Accordingly we extract three metrics for assessment purposes:

- Learning improvement index (LII) = (Q2_score - Q1_score) / Q1_score,
- Normalized difficulty index (NDI) = Q4_score / Q3_score,
- Usability satisfaction index (USI) = (6 - Q5_score) / 5.

The direct assessment is based on two exams conducted during each semester. One question is designed for each lab exercise, and it is separately graded to the scale of 1~5 for assessment purpose. The exams are open-book open-note. Correctly answering of these questions requires a certain degree of understanding of the lab procedures and results. However, some of such questions are not comprehensive to cover all aspects in lab exercises. Therefore there is possibly a discrepancy between learning experience and direct assessment results.

3. Analysis Methodology

Equivalence analysis

To quantitatively analyze the assessment metrics, we introduce a set of hypothesis tests to evaluate the statistical significance of these assessment metrics *between on-campus learning and on-line learning*.

In the hypothesis testing, we calculate the mean and the standard deviation using the following equations,

$$\boldsymbol{\mu_x = \frac{1}{N}\sum_{i=1}^{N} x_i}, \qquad \boldsymbol{\sigma_x = \sqrt{\frac{\sum_{i=1}^{N}\left(x_i - \mu_x\right)^2}{N}}}$$

where $\boldsymbol{x_i}$ is certain assessment metric score, and $\boldsymbol{N}$ is the number of received survey.

Then we formulate three hypotheses as:

1. $\boldsymbol{H}_{10} : \boldsymbol{\mu}_1 = \boldsymbol{\mu}_2$ *vs* $\boldsymbol{H}_{11} : \boldsymbol{\mu}_1 \neq \boldsymbol{\mu}_2$
2. $\boldsymbol{H}_{20} : \boldsymbol{\mu}_1 < \boldsymbol{\mu}_2$ *vs* $\boldsymbol{H}_{21} : \boldsymbol{\mu}_1 \geq \boldsymbol{\mu}_2$
3. $\boldsymbol{H}_{30} : \boldsymbol{\mu}_1 > \boldsymbol{\mu}_2$ vs $\boldsymbol{H}_{31} : \boldsymbol{\mu}_1 \leq \boldsymbol{\mu}_2$

where μ_1 denotes the mean value of certain assessment metric from the on-campus section, and μ_2 denotes the mean value of the assessment metric from the corresponding online section in the same school year.

The test statistic is calculated as follows:

$$t = \frac{\mu_1 - \mu_2}{\sqrt{\frac{\sigma_1^2}{N_1} + \frac{\sigma_2^2}{N_2}}}$$

We conduct the pairwise hypothesis testing between the mean value μ_1 of the on-campus sections and the mean value μ_2 of those on-line sections in each school year. Limiting the comparative study within each school year is intended to compensate the variations in student preparation levels over the years.

For each hypothesis testing, we will accept H_{10} if $|t| < \mathbf{2.345}$, i.e., two set of assessment results are statistically equivalent (where 2.345 is for a two-tailed test where the results are significant with $p = 0.02$ and a one-tailed test where the results are significant with $p = 0.01$). We will accept H_{20} if $t < \mathbf{-2.345}$, i.e., the particular assessment index is more significant in on-line section; and we will accept H_{30} if $t > \mathbf{2.345}$, i.e., this assessment index is more significant in on-campus section.

Correlation analysis

Our correlation analysis aims at extracting the relationships *between student learning experience assessment and direct assessment.*

In this study we use linear regression according to model $y=mx+b$, where x and y are two vectors under study, and interception is set to be zero, i.e. $b=0$. The zero interception is selected because our learning experience assessment and direct assessment are normalized to the same scale between 1~5, and higher score corresponds to higher expectation/achievement.

Under this model, we use least mean square error method to estimate the correlation index m, as

$$m = \frac{\sum (x_i - \mu_x)(y_i - \mu_y)}{\sum (x_i - \mu_x)^2}$$

When m is close to 1, the two variables x and y are almost identical, which indicates a high degree of correlation. When m is smaller than 1, it implies x increases faster than y; and when m is larger than 1, it implies y increases faster than x.

We also calculate the standard error of the estimation σ_e, as

$$\sigma_e = \sqrt{\frac{\sum_{i=1}^{N}(y_i - mx_i)^2}{N}}$$

Higher the value σ_e is, less the regression accuracy is, which means higher degree of variation within the input vectors.

In addition, we calculate the coefficient of determination, or squared correlation coefficient as

$$R^2 = \frac{\sum y_i^2 - \sum(y_i - mx_i)^2}{\sum y_i^2}$$

The range of R^2 is from 0 and 1, and higher value indicates better fit of data to the linear model.

In our study, x is set to be direct assessment results and y is learning experience assessment results. More specifically, we make comparison between four pairs of x and y vectors.

1) S1/D: where x is direct assessment results of whole class, and y is survey results of the whole class on the first survey question, i.e. understanding level ***before*** the lab exercise;
2) S2/D: where x is direct assessment results of whole class, and y is survey results of the whole class on the second survey question, i.e. understanding level ***after*** the lab exercise;
3) S2/D upper 50%: where x and y are the results of direct assessment and the second survey question from the upper 50% of class;
4) S2/D lower 50%: where x and y are the results of direct assessment and the second survey question from the lower 50% of class.

Here S1 denotes Q1 score, S2 denotes Q2 score, and D denotes direct assessment score. The upper 50% of class and lower 50% of class are based on students' overall course grades.

4. Descriptions of the Lab Exercises and Assessment Results

We have collected the student learning experience assessment and direct assessment results from the Fall 2012 and Spring 2013 semesters. The overall average survey scores for each lab exercise are shown in Figures 1~6. The statistical equivalence tests and correlation analysis results are presented in Tables 1~6.

Lab1. Projection and Projection Slice Theorem (tomography)

Student first creates simple 2D objects from isolated points, simple shapes (rectangle, circle, ellipse etc.), and observes their projection (radon) domain presentations. The number and angle of projections are specified by the student. A phantom template is also provided so that student can manipulate the components to created different phantom objects for projection tests. Student then use the phantom object to validate projection slice theorem. The process is to take one projection at student specified angle, then display this projection signal, the 1D FFT of this projection, as well as the corresponding slice of the 2D DFT of the phantom image. Student can observe the consistence of these two FFT results at any selected projection angle.

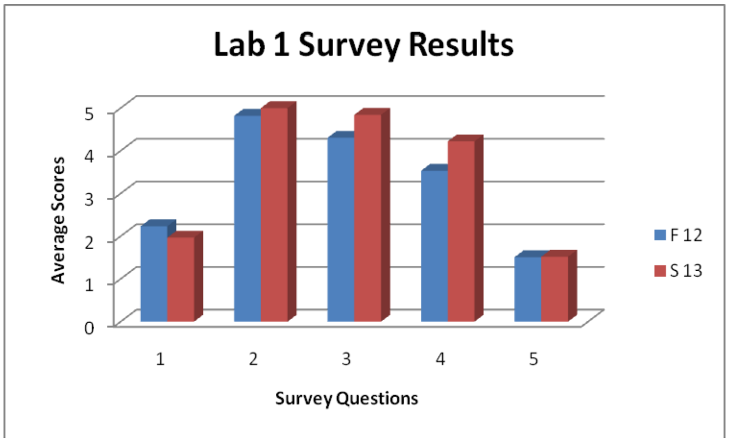

Figure 1. Lab 1 survey assessment results.

Table 1(a). Statistical equivalence tests of Lab 1 assessment metric LII, NDI, USI and Direct Assessment between on campus class and on-line class.

Learning Improvement Index (LII)				
	On Campus (Fall 12)	On Line (Spring 13)	t-score	Hypothesis
Avg	1.253205	1.805556	-1.58884052	H_{10}
Std	1.159377	1.20512		
Normalized Difficulty Index (NDI)				
	On Campus (Fall 12)	On Line (Spring 13)	t-score	Hypothesis
Avg	0.754808	0.879365	-1.088827496	H_{10}
Std	0.26249	0.46815		
Usability Satisfaction Index (USI)				
	On Campus (Fall 12)	On Line (Spring 13)	t-score	Hypothesis
Avg	0.7	0.780952	-1.267809722	H_{10}
Std	0.228035	0.208852		
Direct Assessment				
	On Campus (Fall 12)	On Line (Spring 13)	t-score	Hypothesis
Avg	4.423077	4.0	1.568383164	H_{10}
Std	0.808608	1.0		

Table 1(b). Correlation analysis of Lab 1 assessment results.

Fall 12 On Campus Class				
	S1/D	S2/D	S2/D upper 50%	S2/D lower 50%
m	0.510476	0.906667	0.958955	0.85214
σ_e	0.062453	0.048148	0.073869	0.060749
R^2	0.7277	0.934141	0.933528	0.942519

Spring 13 On Line Class				
	S1/D	S2/D	S2/D upper 50%	S2/D lower 50%
m	0.421348	0.901685	0.756757	1.28866
σ_e	0.090874	0.080865	0.071772	0.123926
R^2	0.518051	0.861432	0.909965	0.931113

In this lab students just began to practice the new knowledge they acquired in this course. The behaviors of learning experience and direct assessment results are relatively easy to interpret. They can be considered as calibration benchmark for understanding and evaluating the results from the following lab exercises.

There are notable and comparable learning improvements (LII) and perceived difficulties (NDI) in both on campus and online sections. The satisfaction (USI) scores are in the normal range of 0.7~0.8. Furthermore, the direct assessment results indicate normal achievement level between 4~5. The statistic equivalence test results show no significant difference between on-campus and on-line sections.

In correlation analysis, we observe that perceived learning score S2 and direct assessment score are closely correlated, i.e. the ***m*** values of S2/D are close to 1. Within the whole class, S2/D is generally a little less than 1, which indicates that the perceived achievement is a little less than the actual achievement. When we look at the upper 50% and lower 50% students separately, we observe clear divergence in S2/D. It appears that on campus students had general better estimation on their achievements than on-line students, and the higher 50% of the class had better estimation on their learning achievement than the lower 50% of the class. In particular, we observe that in on-line section, the lower 50% students had much higher perceived achievement than actual achievement.

Lab 2. Frequency domain reconstruction – number of projects, interpolation methods (x-ray CT, MRI)

Student selects a 2D object and specifies the number of projections, number of samples per projection and projection angles. The projection results are displayed. Each projection is then placed on a 2D frequency domain at corresponding angle, and this process is displayed in both 2D and 3D plots. After all projections are placed into this 2D space, interpolation is performed to create samples at Cartesian grid, and a 2D inverse FFT is performed to generate the reconstruction image. Student is instructed to try a sequence of parameter sets to observe the changes in reconstruction image quality. In particular, frequency domain interpolation can only be observed clearly when number of projections and number of samples per projection are small, but good quality image can only be obtained when these numbers are large. Student will explore these different settings and report the findings.

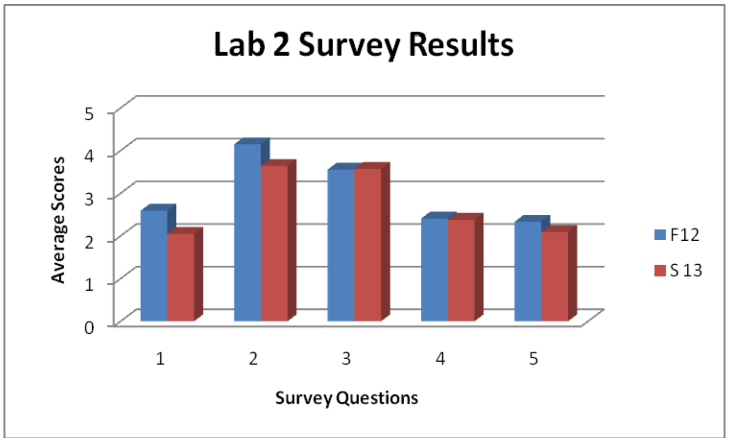

Figure 2. Lab 2 survey assessment results.

Table 2(a). Statistical equivalence tests of Lab 2 assessment metric LII, NDI, USI and Direct Assessment between on campus class and on-line class.

Learning Improvement Index (LII)				
	On Campus (Fall 12)	On Line (Spring 13)	t-score	Hypothesis
Avg	1.012346	1.230159	-0.68533248	H_{10}
Std	1.057559	1.118625		
Normalized Difficulty Index (NDI)				
	On Campus (Fall 12)	On Line (Spring 13)	t-score	Hypothesis
Avg	0.739506	0.726984	0.100238413	H_{10}
Std	0.48585	0.379637		
Usability Satisfaction Index (USI)				
	On Campus (Fall 12)	On Line (Spring 13)	t-score	Hypothesis
Avg	0.733333	0.780952	-0.829999928	H_{10}
Std	0.20755	0.18873		
Direct Assessment				
	On Campus (Fall 12)	On Line (Spring 13)	t-score	Hypothesis
Avg	4.444444	4.571429	-0.392770083	H_{10}
Std	0.974022	1.207122		

Table 2(b). Correlation analysis of Lab 2 assessment results.

Fall 12 On Campus Class				
	S1/D	S2/D	S2/D upper 50%	S2/D lower 50%
m	0.553763	0.897849	0.98556	0.811388
σ_e	0.058117	0.044755	0.034438	0.077611
R^2	0.770779	0.93713	0.98556	0.893703
Spring 13 On Line Class				
	S1/D	S2/D	S2/D upper 50%	S2/D lower 50%
m	0.418803	0.755342	0.7	0.834197
σ_e	0.057871	0.056377	0.052223	0.111757
R^2	0.713787	0.895267	0.947276	0.860934

Lab 2 becomes more sophisticated and deeper into the new subject. Compared with Lab 1, we see a little decrease in learning scores (LII), and about the same in difficulty scores (NDI) and satisfaction scores (USI). We also observe a slight increase in direct assessment score. Again there is still no significant difference between two learning modes. We also observe high correlations between perceived achievement score S2 and actual achievement score D in all sections. Again on campus students had slightly better estimation on their learning achievements.

Lab 3. Filtered back projection – number of projections, filters, noise (x-ray CT)

Student selects a 2D object and specifies a projection angle and number of samples per projection. The 1D projection is displayed. Then student clicks "back-projection", and observes the creation of a 2D back-projection image displayed in both 2D and 3D plots. Student then specifies a series of projection angles, and observed the accumulation of all back-projections into one 2D reconstruction image. Student should see that such reconstruction looks blurred and too bright. Student then selects a filter and applies it to each 1D projection before the back-projection. Student will observe a much clearer reconstruction image from filtered back-projections. Student will further explore different filters, cut-off frequencies of filters, and projections with different levels of induced noise. The filtering effects become more evident. Given the large parameter space, this exercise is rather long and it usually takes students two weeks to complete.

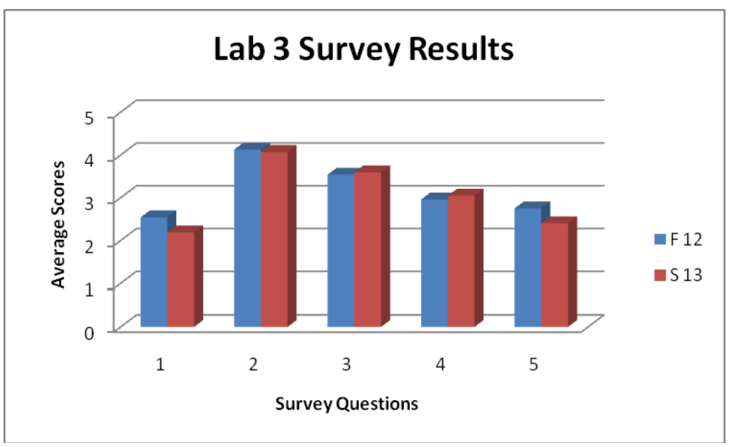

Figure 3. Lab 3 survey assessment results.

Table 3(a). Statistical equivalence tests of Lab 3 assessment metric LII, NDI, USI and Direct Assessment between on campus class and on-line class.

Learning Improvement Index (LII)				
	On Campus (Fall 12)	On Line (Spring 13)	t-score	Hypothesis
Avg	0.965278	1.27381	-0.980340896	$\boldsymbol{H}_{10}$
Std	0.961178	1.127664		
Normalized Difficulty Index (NDI)				
	On Campus (Fall 12)	On Line (Spring 13)	t-score	Hypothesis
Avg	0.950694	0.929365	0.135312965	$\boldsymbol{H}_{10}$
Std	0.585853	0.470606		

Usability Satisfaction Index (USI)				
	On Campus (Fall 12)	On Line (Spring 13)	t-score	Hypothesis
Avg	0.65	0.719048	-1.084261627	H_{10}
Std	0.251949	0.172102		

Direct Assessment				
	On Campus (Fall 12)	On Line (Spring 13)	t-score	Hypothesis
Avg	3.6875	3.142857	1.515886761	H_{10}
Std	1.365829	1.038543		

Table 3(b). Correlation analysis of Lab 3 assessment results.

Fall 12 On Campus Class				
	S1/D	S2/D	S2/D upper 50%	S2/D lower 50%
m	0.645904	1.025051	1.025157	1.024857
σ_e	0.057157	0.064631	0.073233	0.128736
R^2	0.841793	0.912898	0.942297	0.863716

Spring 13 On Line Class				
	S1/D	S2/D	S2/D upper 50%	S2/D lower 50%
m	0.655022	1.187773	1.057915	1.356784
σ_e	0.070271	0.083058	0.073613	0.148135
R^2	0.805355	0.906875	0.958244	0.893492

Lab 3 is an extension to Lab 2. It is more comprehensive, and it concludes the subject of tomographic imaging. Compared with Lab 2, we observed slight decrease in learning scores (LII), and similar and high difficulty scores (NDI). The satisfaction scores (USI) are about the same. The direct assessment scores are also lower than Lab 2. Still, no signification difference between two learning modes is observed.

Here we observe that, although the correlations between perceived achievement S2 and direct assessment D are still very high, the ***m*** values of S2/D are higher than 1, which is in contrast to Lab1 and Lab 2 results. This is partially due to the fact that many students couldn't answer a challenging question in the exam. Again, on campus students had better estimation in their learning achievements.

Lab 4. X-ray attenuation coefficient and survival probability (x-ray)

Student selects a material from ("adipose", "air", "aluminum", "bone", "copper", "iodine", "lead", "lung", "muscle", "soft tissue", "water"), and changes the incident x-ray energy from 10 to 400 KeV. The mass attenuation coefficient is displayed for each material at each x-ray energy level. Absorption edges for some materials can be observed when the energy increment is small. In the second part, student selects a metal material, an incident x-ray energy and changes the thickness of the material to observe the numbers of survival x-ray photons after the penetration. The results are based on NIST dataset, and there is not much computation involved.

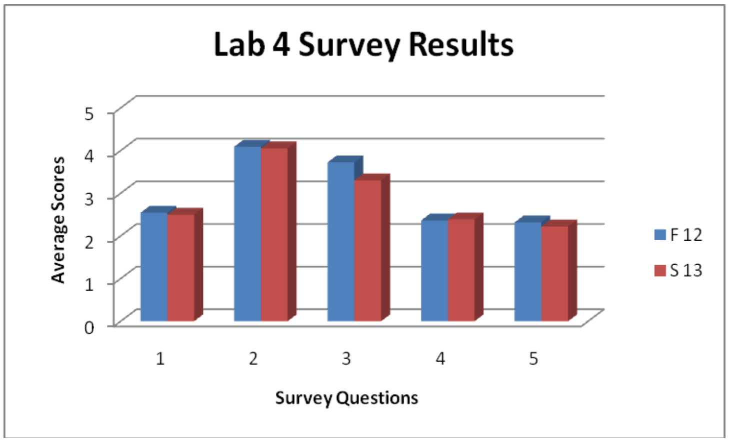

Figure 4. Lab 4 survey assessment results.

Table 4(a). Statistical equivalence tests of Lab 4 assessment metric LII, NDI, USI and Direct Assessment between on campus class and on-line class.

Learning Improvement Index (LII)				
	On Campus (Fall 12)	On Line (Spring 13)	t-score	Hypothesis
Avg	1.011364	0.981481	0.101231326	H_{10}
Std	1.033274	0.833606		
Normalized Difficulty Index (NDI)				
	On Campus (Fall 12)	On Line (Spring 13)	t-score	Hypothesis
Avg	0.673485	0.95	-1.246431296	H_{10}
Std	0.324716	0.894208		
Usability Satisfaction Index (USI)				
	On Campus (Fall 12)	On Line (Spring 13)	t-score	Hypothesis
Avg	0.736364	0.755556	-0.292786769	H_{10}
Std	0.198915	0.212055		
Direct Assessment				
	On Campus (Fall 12)	On Line (Spring 13)	t-score	Hypothesis
Avg	4.318182	3.611111	1.464708455	H_{10}
Std	1.286796	1.685191		

Table 4(b). Correlation analysis of Lab 4 assessment results.

Fall 12 On Campus Class				
	S1/D	S2/D	S2/D upper 50%	S2/D lower 50%
m	0.548315	0.889888	0.92	0.851282
σ_e	0.062475	0.05499	0.044222	0.107281
R^2	0.777842	0.922501	0.97963	0.851282
Spring 13 On Line Class				
	S1/D	S2/D	S2/D upper 50%	S2/D lower 50%
m	0.600707	0.954064	0.846995	1.15
σ_e	0.089583	0.100453	0.132535	0.157123
R^2	0.714127	0.833648	0.836205	0.870066

Lab 4 is quite different from Lab 1~3, and it is more related to physics than mathematics. Also it is relatively simpler. Therefore we observe slightly increased difficulty scores (NDI). The improvement score (LII) and the satisfaction scores (USI) are about the same. However the direct assessment scores are notably increased. The statistical equivalence tests still indicate no significant difference between on campus and on-line sections.

The correlations between perceived learning achievements and actual achievements remain strong. The behavior is similar to Lab 1, with the lower 50% students in the on-line section having significantly higher estimation about their achievement than other students.

Lab 5. NMR signals – precessions, relaxation, basic sequences (MRI)

Student first gets familiar with 3D vector representation of spin magnetization, by specifying an excitation on the equilibrium vector Mz, and observing the resulting 3D vector. Then student will observe spin dynamics including transverse (T2) relaxation, longitudinal (T1) relaxation, and free precession individually and jointly. Student specifies T1, T2 times, initiates an excitation angle, and then observes the vector changes over time, typically for a range of 1 ~ 2400 ms. The display is progressive for 10 frames per second. At the same time, the student will also observe the FID (free-induced-decay) signal waveform generated from each session. In the second part, student simulates some basic NMR sequences, including saturation recovery (SR) and spin echo (SE). In SR simulation, student specifies the T1, T2 values, an excitation angle, the repetition time (TR), echo time (TE), and repetition number. Student will observe the vector animation and FID that is generated. In SE simulation, student specifies number of spins, e.g. 10, off-resonance frequencies randomly distributed between -50 Hz and 50 Hz. Student can observe the animation of all these spin vectors and the aggregated FID signals. In particular, this simulation is very helpful in explaining the divergence and refocus of magnetization on x-y plan in SE. This exercise is also very long, and it usually takes students two weeks to complete.

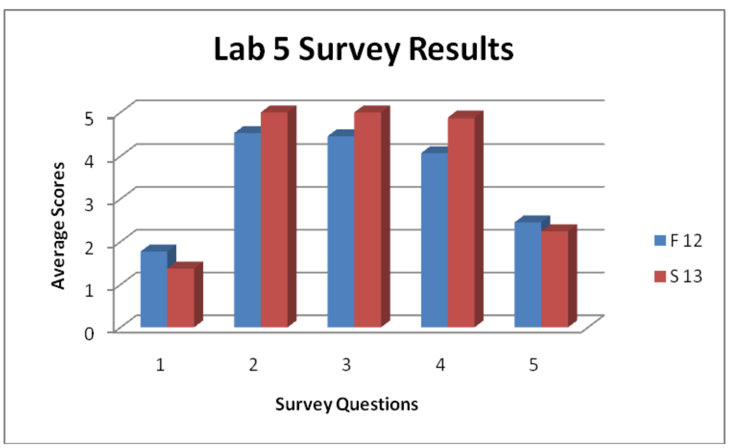

Figure 5. Lab 5 survey assessment results.

Table 5(a). Statistical equivalence tests of Lab 5 assessment metric LII, NDI, USI and Direct Assessment between on campus class and on-line class.

Learning Improvement Index (LII)				
	On Campus (Fall 12)	On Line (Spring 13)	t-score	Hypothesis
Avg	0.759615	1.546296	-2.646155775	H_{20}
Std	0.704875	1.116653		
Normalized Difficulty Index (NDI)				
	On Campus (Fall 12)	On Line (Spring 13)	t-score	Hypothesis
Avg	1.166667	1.030556	0.802578249	H_{10}
Std	0.649786	0.474763		
Usability Satisfaction Index (USI)				
	On Campus (Fall 12)	On Line (Spring 13)	t-score	Hypothesis
Avg	0.630769	0.694444	-0.955795234	H_{10}
Std	0.231118	0.207144		
Direct Assessment				
	On Campus (Fall 12)	On Line (Spring 13)	t-score	Hypothesis
Avg	4.807692	4.555556	0.789999419	H_{10}
Std	0.633671	1.247219		

Table 5(b). Correlation analysis of Lab 5 assessment results.

Fall 12 On Campus Class				
	S1/D	S2/D	S2/D upper 50%	S2/D lower 50%
m	0.466448	0.711948	0.723077	0.699301
σ_e	0.038919	0.033943	0.03608	0.061876
R^2	0.846738	0.944199	0.970989	0.914119
Spring 13 On Line Class				
	S1/D	S2/D	S2/D upper 50%	S2/D lower 50%
m	0.36	0.74	0.726852	0.755435
σ_e	0.051586	0.051316	0.047411	0.100928
R^2	0.730141	0.920336	0.967083	0.875045

Lab 5 is the most challenging lab exercise, because it is mostly mathematical and abstract. We observe relatively low learning scores (LII), high difficulty scores (NDI) and low satisfaction scores (USI). The direct assessment scores remain to be normal. One of the reasons is that the related exam question was not comprehensive on the subject and was relatively simple, so most students received very good marks. Here we observe a statistical in-equivalence between on campus section and on-line section in LII scores. On-line students appeared to be much more optimistic on their learning improvement.

In the correlation analysis, the behavior of the m values is in opposite to that in Lab 3. Here the m values are all around 0.7, which indicates that students' perceived learning achievements are much lower than their actual achievement. It is due to the fact of a simple exam question.

Lab 6. Brain activation detection in fMRI (image analysis)

Student is given a functional MRI dataset containing one axial brain slice for 68 time samples. Each image is of 46 by 55 in size. The data was collected by a 1.5T GE Echo Speed Horizon scanner for a finger-tapping test. The paradigm contains 4 on-periods and 5-off periods, which is explained to the student. The first image is displayed, and the student can click any pixel on the image to display the time sequence of that pixel. In the lab instruction, a few active pixels are listed, and student can locate these pixels and see the similarity of these time sequence with the paradigm. Then student is asked to find a few more active pixels, e.g. five. A t-test tool is provided, so student can obtain the t-value for any selected pixel, and can observe that higher t-values correspond to higher similarity between the selected pixel and the paradigm.

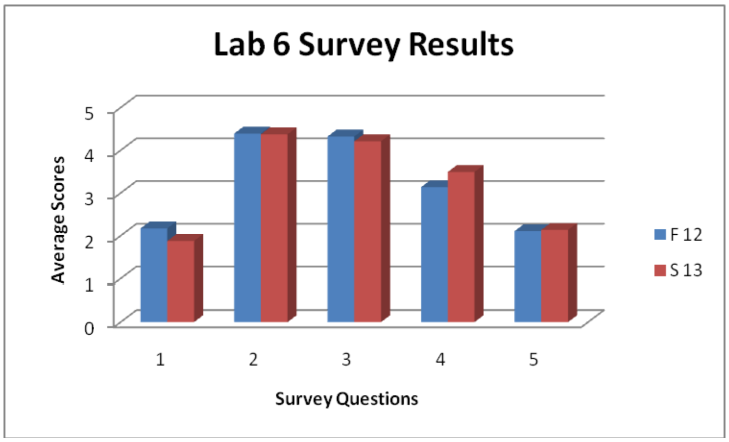

Figure 6. Lab 6 survey assessment results.

Table 6(a). Statistical equivalence tests of Lab 6 assessment metric LII, NDI, USI and Direct Assessment between on campus class and on-line class.

Learning Improvement Index (LII)				
	On Campus (Fall 12)	On Line (Spring 13)	t-score	Hypothesis
Avg	1.496212	1.22619	0.71975125	$\boldsymbol{H}_{10}$
Std	1.216747	1.241958		
Normalized Difficulty Index (NDI)				
	On Campus (Fall 12)	On Line (Spring 13)	t-score	Hypothesis
Avg	0.665152	0.63254	0.188660213	$\boldsymbol{H}_{10}$
Std	0.47325	0.643201		
Usability Satisfaction Index (USI)				
	On Campus (Fall 12)	On Line (Spring 13)	t-score	Hypothesis
Avg	0.718182	0.804762	-1.431004745	$\boldsymbol{H}_{10}$
Std	0.21075	0.185678		
Direct Assessment				
	On Campus (Fall 12)	On Line (Spring 13)	t-score	Hypothesis
Avg	4.272727	3.333333	2.110888949	$\boldsymbol{H}_{10}$
Std	1.420323	1.494434		

Table 6(b). Correlation analysis of Lab 6 assessment results.

Fall 12 On Campus Class				
	S1/D	S2/D	S2/D upper 50%	S2/D lower 50%
m	0.391892	0.806306	0.855932	0.75
σ_e	0.063034	0.073202	0.0826	0.129719
R^2	0.637282	0.846503	0.914806	0.769737
Spring 13 On Line Class				
	S1/D	S2/D	S2/D upper 50%	S2/D lower 50%
m	0.658273	1.032374	0.974843	1.109244
σ_e	0.087342	0.095916	0.064207	0.197845
R^2	0.730085	0.846547	0.962424	0.758654

Lab 7 is different from all other lab exercises. It presents an interesting real-world application. Students appeared to enjoy it over the years. We observed high learning scores (LII), and modest difficulty score (NDI) and satisfaction scores (USI). The direct assessment scores remain normal. No significant difference between the two learning modes.

On campus students once again had lower estimation about their achievements than on line students, and the lower 50% students in the online section still had the highest estimation.

5. Assessment Discussions

Overall we think the results match our expectation well. We see clear indications of improved understanding of the topics under investigation across all sections. From Question 3~5 results we see that most of the students appeared to be satisfied with the implementation and usability of the software, although the complain of "too much time spent" can be observed from Question 4 results, especially in Lab 5.

More specifically, from the results we have the following consistent observations:

1. On most of the assessment metrics, statistical equivalence tests reveal that there is no significant difference between on campus and online section. In particular, the LII scores are quite close between on-campus sections and on-line sections, which suggests that the software labs can provide comparable learning experience to both student groups.

2. In correlation analysis, we observe that perceived learning score S2 and direct assessment score are reasonably correlated, i.e. the ***m*** values of S2/D are close to 1. When all students are considered, S2/D is usually a little less than 1, which indicates that the perceived achievement is a little less than the actual achievement.

3. We also observe that on campus students had general better estimation on their achievements than on-line students, i.e. the ***m*** values of S2/D are closer to 1 in on-campus section than in on-line section. This observation may have a significant implication, i.e. although both on campus students and online students obtained similar learning experience and achievement, online students have some disadvantage in correctly estimating their actual progress.

4. When we look at the upper 50% and lower 50% students separately, the upper 50% of the class had better estimation on their learning achievement than the lower 50% of the class.

5. We observe that online students tended to be more optimistic on their learning achievements, and on campus students appeared to be more pessimistic. However, their direct assessment scores are usually comparable. We do not intend to generalize this observation, and we will continue this study to better understand this phenomenon.

In many cases it is very difficult to make conclusive statement given the current assessment data. We will continue our studies in the following years. Given our unique advantage of having two sections of the same course, one on campus and one online, we believe that our continuous comparative study will produce helpful findings to the entire online learning community.

6. Conclusion

We designed a series of computer lab exercises using SimuRad for an undergraduate medical imaging course, which is regularly offered both on-campus and on-line. Assessments on these labs were obtained through student surveys and exam questions. We studied the assessment results and obtained some interesting findings. The results generally indicate that this software is a helpful learning tool and its usability is satisfactory. We also observed that students' learning behaviors are slightly different in some instances between the on-campus sections and the on-line sections. We believe that some observations call for further investigations, which may provide insights for developing more effective learning tools, especially for online learning.

Bibliography

1. J. T. Bushberg, J. A. Seibert, E. M. Leidholdt, and J. Boone, *Essential Physics of Medical Imaging* (2nd Ed), Lippincott Williams & Wilkins, 2002.
2. A. Louie, J. Izatt, and K. Ferrara, "Biomedical Imaging Graduate Education Programs: Imaging Curricula and Imaging Courses", the Whitaker Foundation Biomedical Engineering Education Summit, 2005, http://www.whitaker.org/academic/wrapup.html.
3. C. B. Paschal, "The Need for Effective Biomedical Imaging Education", *IEEE Engineering in Medicine and Biology Magazine*, Vol. 22, Num. 4, pp. 88-91, July/August 2003.
4. J. E. Greenberg, B. Belgutte, and M. L. Gray, "Hands-On Learning in Biomedical Signal Processing", *IEEE Engineering in Medicine and Biology Magazine,* Vol. 22, Num. 4, pp. 71-79, July./August 2003.
5. H. Man and A. Ritter, "Computed Tomography in SimuRad – A Medical Imaging Simulation Software", ASEE Annual Conference 2009, Austin TX, Aug. 2009.
6. H. Man, "Understanding the Difference between Classroom Learning and Online Learning on Medical Imaging with Computer Lab Exercises", ASEE Annual Conference 2012, San Antonio TX, June 2012.
7. M. H. DeGroot and M. J. Schervish, *Probabilities and Statistics* (3rd Ed), Addison-Wesley, 2002.