Taking Advantage of Low Enrollment Scheduled Courses for the Integration of Research and Teaching

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Abstract - **This paper presents a case study on the viability of turning a course with low enrolment into an opportunity for a research project based course that effectively combines teaching and research for undergraduate students. The advantages, disadvantages, and issues encountered are discussed based on experiences acquired at The College of New Jersey during a special topics class on Digital Image Processing. The overriding goal was to take advantage of a regularly scheduled class with low enrolment to provide students with powerful learning experiences that they can easily transfer to graduate school and/or a future workplace. The advantages of using this approach are numerous, as it turns a situation that can potentially de-motivate students into a win-win scenario for the faculty and the students. Conclusions on the approach of combining research and teaching in a fixed time frame setting are derived taking into account student feedback for this type of course.**

Index Terms - Undergraduate Education, Design Education, Research Education.

INTRODUCTION

As new technologies are developed, educational institutions still have the responsibility to equip students with a well-balanced education. This balance must consist of a solid coverage of the fundamentals, and additionally, a coverage and perspective of these new technologies. This paper presents a case study on the viability of using a scheduled course with low enrolment into a research project based course that effectively combines teaching and research for undergraduate students. The advantages, disadvantages, and issues encountered are discussed based on experiences acquired at The College of New Jersey (TCNJ) during a senior level special topics class on Digital Image Processing (DIP). The overriding goal was to take advantage of a regularly schedule class with low enrolment to provide students with powerful learning experiences that they can easily transfer to graduate school and/or a future workplace. The advantages of using this approach are numerous, as it turns a situation that can potentially de-motivate students into a win-win scenario for the faculty and the students. Since the time for the project is fixed, and therefore real time constraints exist, care must be taken that the scope and length of the project are carefully selected, so that the students can accomplish tasks during the semester that are both challenging and accomplishable during the timeframe available. Other important issues are raised and encountered, and they are discussed in this paper. Issues such as the level of preparation or pre-requisite knowledge that the students must have so that this model is successful; how to continuously through the semester provide grading feedback to students, so they do not have to wait until the turning of a report at the end of the semester to know their standing in the course; and the reaction of student to the intensity of such a course from the perspectives of breath, depth, and level of difficulty of assignments that mirror those that can be expected to be received in the workplace. Conclusions on the approach of combining research and teaching in a fixed time frame setting are derived taking into account student feedback on this type of course.

PLAN OF ATTACK

The first step in this approach is to propose to student the changing of the course format from a traditional course to one where a bounded research project is going to be done. It is important to get their buy-in at the beginning of the course and to assure them that they will be successful, and that the instructor will lecture and give them hands on exercises to fill any background gaps that they may have. This is best accomplished by working side-by-side with the students, which is feasible given that the number of students is small (less than 5). For example, the whole project was done using the C programming language, and the instructor was able to work with the students to teach them advanced debugging techniques that are not taught in the required programming courses for undergraduate engineering students due to lack of time during those courses.

It is also important to give the students as much information as possible at the beginning, and this can be done by presenting a clear "Problem Statement", and the different approaches that should be investigated. In our case the problem statement was presented as follows:

Problem Statement:

- Given a database of color texture images, assign each image to a given texture class.
- The number of texture classes is known a priori (supervised classification).
- Use different combinations of random field color texture model features and neural network classifiers.

The students were also presented with different types of approaches that could be taken for the investigation. This is shown in Tables I and II. The overall approach is shown in Fig. 1 and a program management framework is shown in Fig. 2. This last aspect is important to ensure that the students are aware that there is a bounded timeframe to execute the project (i.e. the semester during which the course is running). It is also equally important that the faculty chooses an amount of work that can be accomplished in the timeframe, so that the students achieve. The faculty should also commit to the project as much time as necessary to enable students' success. Different parts of the project were assigned to different students, although they all participated and benefited from the lectures on the basic Digital Image Processing topics, and the advanced topics needed for the whole team to do the project. One student was in charge of the database creation and management, another created the color texture features, a third created the grey-level classification, and the fourth designed the neural network for the color texture classification.

Tables I and II proposed different approaches to do the color texture classification and to compare it to grey level texture classification. This enhanced the open ended aspect of the research where students are not told to follow a specific approach, but are asked to consider multiple combinations of Neural Networks and Features to perform the color texture classification, and compare the performance to that of a classic grey level texture classification approach. Fig. 1 shows the overall workflow for the research project that was followed for the color texture classification for the different features. Although this is a well known workflow for supervised applied imagery pattern recognition, the students and the instructor developed it together as a team, rather than the instructor giving the work model to the students. Again, this enhanced the creative aspects of the research project.

The students and the instructor worked together for at least four hours per week, and during this time students were provided with feedback on their work and their progress toward achieving milestones. The students also worked on their own for periods of time beyond this where the instructor was available on an as needed basis. This fostered a level of independence for the students, while maintaining adequate support from the instructor. The course started with a two weeks period of lectures on the fundamentals of Digital Image Processing. Then throughout the semester, the students were assigned readings of research papers related to the research project, and these were discussed as a group during class times. The student's oral presentations of these papers were graded as part of the overall grading framework for the course. This forced and challenged the students to stretch their capabilities to study and understand advanced technical literature. Other formal lectures followed during the course to cover advanced topics that that students needed to be successful in their research. Examples of these topics were formal lectures and assigned exercises in grey level texture classification via Grey Level Co-Occurrence Matrix (GLCM), and Artificial Neural Networks with Back-Propagation training algorithms.

TABLE I
PROJECT PROPOSAL WITH A 3-LAYER NEURAL NETWORK

DATABASE	**FEATURES**	**CLASSIFIER**
COLOR	MSAR: ½ NEIGHBORHOOD F NEIGHBORHOOD	3 LAYERS WITH BACK-PROPAGATION TRAINING
COLOR	MMRF: ½ NEIGHBORHOOD F NEIGHBORHOOD	3 LAYERS WITH BACK-PROPAGATION TRAINING
COLOR	PMRF: ½ NEIGHBORHOOD F NEIGHBORHOOD	3 LAYERS WITH BACK-PROPAGATION TRAINING
GREY-LEVEL	GLCM	3 LAYERS WITH BACK-PROPAGATION TRAINING

TABLE II
PROJECT PROPOSAL WITH A 4-LAYER NEURAL NETWORK

DATABASE	**FEATURES**	**CLASSIFIER**
COLOR	MSAR: ½ NEIGHBORHOOD F NEIGHBORHOOD	4 LAYERS WITH BACK-PROPAGATION TRAINING
COLOR	MMRF: ½ NEIGHBORHOOD F NEIGHBORHOOD	4 LAYERS WITH BACK-PROPAGATION TRAINING
COLOR	PMRF: ½ NEIGHBORHOOD F NEIGHBORHOOD	4 LAYERS WITH BACK-PROPAGATION TRAINING
GREY-LEVEL	GLCM	4 LAYERS WITH BACK-PROPAGATION TRAINING

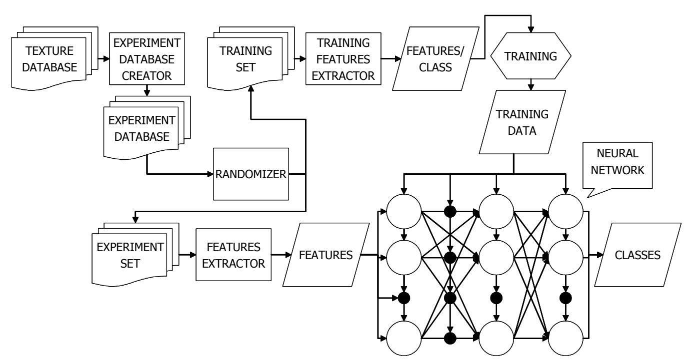

FIGURE 1
OVERALL APPROACH.

ID		Task Name	Duration	Start	Finish
1		Introduction / Kick-off	1 wk	Tue 1/20/04	Mon 1/26/04
2		Setpu Work Area	1 wk	Tue 1/27/04	Mon 2/2/04
3		Work out interfaces	1 wk	Tue 2/3/04	Mon 2/9/04
4		Design Database	2 wks	Tue 2/10/04	Mon 2/23/04
5		Divide Database	1 wk	Tue 2/24/04	Mon 3/1/04
6		**Generate Features**	**40 days**	**Tue 2/3/04**	**Mon 3/29/04**
7		MSAR	5 wks	Tue 2/3/04	Mon 3/8/04
8		MMRF	6 wks	Tue 2/10/04	Mon 3/22/04
9		PMRF	6 wks	Tue 2/17/04	Mon 3/29/04
10		GLCM	5 wks	Tue 2/3/04	Mon 3/8/04
11		**Generate NN Results**	**50 days**	**Tue 2/3/04**	**Mon 4/12/04**
12		3 Layers	5 wks	Tue 3/9/04	Mon 4/12/04
13		4 Layers	10 wks	Tue 2/3/04	Mon 4/12/04
14		Write Reports	3 wks	Tue 4/13/04	Mon 5/3/04
15		Turn in Reports	0 days	Mon 5/3/04	Mon 5/3/04

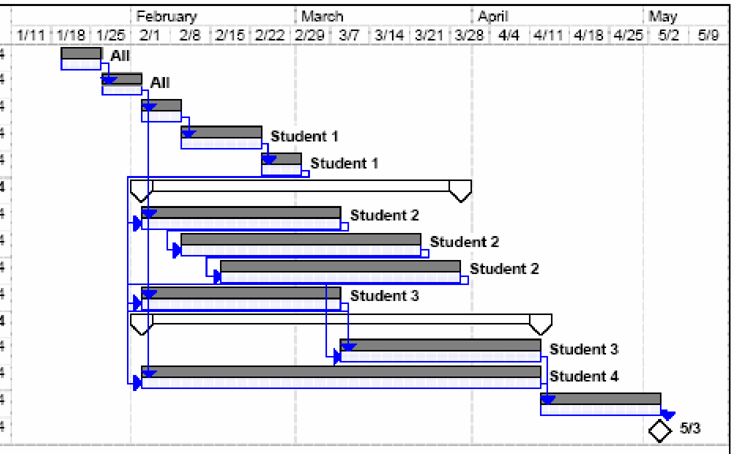

FIGURE 2
PROJECT GANT CHART.

Grading is also an important topic that should be discussed at the beginning of the course, and this represents several challenges. First, it should not be solely tied to the end report, as the students should be given feedback throughout the course, and second, it should include a component of timeliness, so that the students are motivated to execute in a timely fashion. This is tied to the timing boundary conditions imposed by the project being done during a regularly scheduled course. Again, it is of the outmost importance that the faculty is committed to supporting the students, so that they do not get behind. In our case the course grading was structured as follows:

Grading:

- Discussions of Papers
  - Less than 10
  - 10% of Final Grade
- Timeliness
  - How on time you do your work throughout the semester and turn in your report
  - 30% of Final Grade
- Report
  - At least 10 pages not including front page matter (Title, Author, etc.)
  - Double Spaced, 12 points Times New Roman Font
  - Write substance, not wordy!, don't blow up figures
  - 60% of Final Grade
  - Quality of results
    - 30% of Final Grade
  - Substance of your write-up
    - 20% of Final Grade
  - Quality of your write-up
    - 10% of Final Grade

THE PROJECT AND THE RESULTS

A number of texture classification approaches have been developed in the past but most of these studies target gray-level textures. In this work, novel results are presented on Neural Network based classification of color textures in a very large heterogeneous database. Several different Multispectral Random Field models are used to characterize the textures. The classifying features are based on the estimated parameters of these model and functions defined on them. The approach is tested on a database of 73 different color textures classes. The advantage of utilizing color information is demonstrated by converting color textures to gray-level ones and classifying them using GLCM based features.

Classification of textures has become a significant topic of research. There are many different approaches that have been studied due to the usage of different models for extracting features from texture images. From past research, it has been observed that classification of color textures improves the accuracy of classification over gray-level. In the experiments preformed in this work, both color and gray-level models were used to determine the features of the images. The features extracted were then used with a neural network for the classification of the texture images, and new results are presented for this combination of features, classification methodology, size of database, and number of classes.

The color texture models used for feature extraction are Multispectral Simultaneous Autoregressive (MSAR), Multispectral Markov Random Field (MMRF), and the Pseudo-Markov Random Field (PMRF) model. For each of the color texture models, a half and full neighborhood set is used. The features obtained are used by a neural network to distinguish the 73 different texture classes present in a very large heterogeneous database with minimum training of the neural network, and these results are the main novel contribution of this work.

The advantage of considering color in texture classification is also demonstrated in this work. An equivalent gray-level database is created for the color database used in this study. The gray-level textures are then classified using features derived from the GLCM with distances of one and two pixels, and the classification performance of the neural network is compared to that obtained for color textures. There is considerable gain in classification accuracy indicating that color information does provide substantial advantage to the recognition task for a very large heterogeneous database with minimum training of the neural network.

During the initial discussion with students it was decided that both proposed set of experiments with a 3 and a 4-layer Neural Network would not be able to be performed in the timeframe available. At this point, the students were enthusiastic enough about the prospects of the project that they chose to do the more challenging 4-layer Neural Network set of experiments. Thus the work was divided equally by the faculty among the students. The different parts of the work are described in the next subsections. The faculty was also careful to match the skill level and individual background brought into the course by each student with the level of difficulty of each student's part of the project.

I. Image Database Construction

For our study, the VisTex database was used [1]. These are prepackaged images and considered as one of the standard image databases for color texture processing. It is comprised of many reference textures and real-world textures. A real-world texture is an image where various textures appear. A reference natural texture is basically homogeneous, and this is what this study employs.

From the VisTex database, a maximum of 73 texture classes were able to be extracted. Database images with a size of 512 x 512 pixels were decimated into 64 x 64 pixels sub-images to populate the final database. Therefore, each larger texture image was fragmented into 64 square sub-images.
So each 512 x 512 image supplies 64 texture samples. There are a total number of 120 images that can be used from the VisTex database, which yielded a database of 7,680 texture images with 73 texture classes. With this approach, not all texture classes have the same number of texture image members, but the average number of samples or members per texture class is 105.

After the color database has been generated, there must be a grey scale counterpart to it for GLCM. A second database of gray-level textures is generated from this color database by converting all of the 7,680 color images into gray-level ones. The database is then separated into a "training" set and a "test" set. The training set has about a randomly chosen 1/3 of all the images available, while the test set has the rest of the images in the database. The training set is used to train the neural network, and once the neural network's weights have been set, results are obtained from the test set.

II. Multispectral Random Field Models

Multispectral Random Field Models are the generalization of the gray-level random field models. They were initially developed in [2], [3]. These models are capable of characterizing color textures and are able to synthesize a color texture from the estimated parameters of the model fitted to it [3], [2]. In this work, we utilize three such models for the classification task.

III. Features for Grey-Level Textures

The grey-level version of each of the color textures considered in this study is also generated using the conversion method discussed previously. In this study, GLCM was used. GLCM takes an image with a known number of grey-levels and calculates the frequency of the gradient of color between pixels; effectively calculating a 2-D histogram. After this histogram is calculated, the values are divided by the total number of pixels so that the GLCM becomes a listing of relative probabilities. Finally, the probability matrix is read and manipulated such that features corresponding to texture properties of the image can be calculated.

To calculate the GLCM, the image is analyzed by starting at the upper left-hand corner, at location (0, 0), and then sequentially read in a raster scan fashion. An angle of analysis for the second pixel must also be used: 0, 45, 90, and 135 degrees were used. Because the GLCM calculation uses absolute values to determine the grey-level gradient, angles of 180, 225, 270, and 315 degrees are obtained from their symmetric counterparts. Additionally, using these angles makes the features somewhat rotation invariant. In this project, distances of 1 and 2 pixels were used, since they are typical values for the GLCM technique. After the $\mathrm{GLCM}(d,\theta)$ matrices are obtained, then the probability matrices $P(x,y,d,\theta)$ are calculated.

Finally, features are derived from the P matrix. While GLCM methods have been devised for over 50 different types of features, for this experiment, Contrast, Entropy, Energy, and Correlation were chosen.

Calculating features from GLCM methods is a relatively straightforward and fast algorithm. When GLCM is employed, the image must be of a minimum size (32 by 32), or else there will not be sufficient information to derive an accurately classifiable feature set.

IV. Classification Method

To achieve the classification, a neural network was selected, which was trained with the training set of the database (about 30% of the total number of images). A fully connected 4-layer network is being used in this study; it employs 2 hidden layers, and the hyperbolic tangent was used as the decision function.

V. Classification Results

The neural network classification results are shown in Table III. The number of correctly classified samples out of the total of 5,120 (~70% of the total database) tested samples is shown for the color and gray-level images for features derived from different models.

TABLE III
SUMMARY OF NEURAL NETWORK CLASSIFICATION RESULTS FOR 64X64 IMAGES

Model Type	No. of Correctly Classified Out of 5,120	Accuracy Rate
Color Image Database		
MSAR (half neighborhood)	3,277	64.0%
MSAR (full neighborhood)	4,567	89.2%
MMRF (half neighborhood)	3,645	71.2%
MMRF (full neighborhood)	4,623	90.3%
PMRF (half neighborhood)	3,574	69.8%
PMRF (full neighborhood)	4,628	90.4%
Gray-Level Image Database		
GLCM (1 pixel distance)	2,299	44.9%
GLCM (2 pixels distance)	2,017	39.4%

These results demonstrate that very high classification (in the 90% range) can be achieved for 64×64 color texture images using features of MSAR, MMRF, or PMRF models with a simple 8-pixels neighborhood. This high classification rates are obtained on a very large heterogeneous color texture database with minimal training of a neural network. Considering the results for both neighborhoods, it may be concluded that the features based on the full neighborhood, rather than those based on the half neighborhood, would be the best choice for the classification task.

As for classification results of the gray-level counterpart images, the accuracy rates are well below 50% for both sets of GLCM based features. By comparing the classification results of color images to their gray-level converted counterparts, the advantage of using color becomes apparent. The color results are clearly better. While the color textures are classified in the 90% range, the rate for gray-level images is below the 50% range. When only grey-level information is considered for texture classification, the textural details within a single plane can become fuzzy, and interaction between different image planes becomes more dominant. Inter-plane interactions are efficiently captured by the multispectral models causing them to perform better than the single plane, gray-level features.

The quality of these results was at a level that allowed a paper to be submitted to an international peer reviewed journal in the subject matter [4]. Both the faculty and the students were coauthors in this submission, which greatly enhanced and differentiated students resume, and qualifications for graduate school.

DISCUSSION AND CONCLUSIONS

In this work three different multispectral random field models, MSAR, MMRF, and PMRF, are used for supervised color texture classification. Features are defined on the estimated parameters of these models fitted to the images. These models capture both inter-plane and intra-plane interactions of image pixels resulting in richer characterization of the image compared to the gray-level only GLCM based features. The performance is tested on a large database of 5,120 images and 73 classes. It is shown that a small and compact neighbor set is all that is needed for the classification task. In a neural network based classification scheme and utilizing normalized features, very high classification in the 90% range is obtained for 64×64 images.

To show the advantage of incorporating color (multi-plane activity) in the classification task, gray-level counterparts of the color texture images are created and classified using GLCM based features. It is shown that the classification result is inferior to that of color textures.

In addition to supervised classification applications, the discussed features are particularly attractive in image segmentation tasks. The requirements in the image segmentation applications are often diametrically opposed; the desire for a large number of image features to accurately identify uniform texture regions versus the need for a spatially compact neighbor set to allow accurate detection of texture boundaries. Based on the results of this study, the multispectral random field based approach can satisfy both requirements providing a good tool for image segmentation.

This project was done as the basic content of a low enrolment course in DIP to integrate teaching and research for undergraduate students. The receptiveness of the students to this approach is demonstrated by the anonymous ratings and comments of the students on the course. The ratings are shown in Table IV. These ratings are well above the traditional average of 3.5 on a maximum scale of 5.0. Specifically, the students responded the most positive about the organization of the activities and how the project challenged them to think. While the sample size was necessarily small for the quantitative assessment, because the premise was to work with a small class size, it is significant that the positive response by the students was unanimous. There were also other non-quantitative feedback mechanisms to the instructor about the positive impact of the course for the students. In the written anonymous feedback section of the course evaluation, students highlighted how a course structured in this fashion, as a learn-by-doing an advanced topic, kept them engaged, and how the teaming aspects of the course provided a very positive experience. One of the students even went on to pursue and expand this research topic in graduate school, and another student is getting a job in Image Processing. It is also significant that even though this research project stretched the student's capabilities, there were no signs of frustration from the students. Student frustration was not observed either during the student-instructor interaction or via the anonymous feedback; rather the student experience embodied all positive comments.

TABLE IV
COURSE EVALUATION BY STUDENTS

Parameter or Class Attribute	Rating
ORGANIZATION	4.75
USAGE OF CLASS TIME	4.50
CHALLENGE LEVEL	4.50
THE COURSE ACTIVITIES HELP ME LEARN	4.50
GRADING SCHEME	4.50
THE ACTIVITIES PROVIDE MEANINGFUL FEEDBACK	4.50
THE ACTIVITIES HELPS ME UNDERSTAND	4.50
INTERACTION WITH OTHER STUDENTS	4.00
THE COURSE CHALLENGES ME TO THINK	4.75
OVERALL COURSE EFFECTIVENESS	4.75

The experience of the students was also enhanced and expanded with in-class, College-wide, and regional presentations; and the publishing of a research paper in an international peer-reviewed journal on the subject matter. The feedback from the students, the quality of the project results, and the production of the journal paper lead to the conclusion that a low enrollment course can be turned into a research project to integrate research and teaching, as long as the project is well defined and bounded for the available timeframe, the faculty dedicates enough time in and outside the classroom to enable students' success, and the faculty exerts enough motivation and program management to lead the students to achieve the goals of the project by the end of the semester.

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