TEXTURE DESCRIPTOR VISUALIZATION THROUGH SELF-ORGANIZING MAPS: A CASE STUDY IN UNDERGRADUATE RESEARCH

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Abstract *— The relative inexperience of typical undergraduate students coupled with the demands of graduate students often limits significant research opportunities for undergraduates. Indiana University South Bend has implemented a variety of programs that, collectively, provide pathways from proposal and grant application through publication. Here we feature a project involving the visualization of image texture descriptors as a case study for this process. Visual texture descriptors encode information about the underlying image for typically repetitive patterns such as textiles, wood grain, and masonry. Using Kohonen's self-organizing map for unsupervised cluster visualization, regions sensitive to similar textures are produced, providing insight into their discriminating potential. In this paper we use this undergraduate project as a foundation to describe the programs, process, infrastructure, results, and publication, along with a critique of the strengths and weaknesses of the undergraduate research program.*

Index Terms — Undergraduate, research, self-organizing map, undergraduate publication.

INTRODUCTION

The value of research for undergraduate Computer Science students is widely recognized. The ABET/CSAB guidelines, for example, encourage undergraduate research as a significant component of their education [1]. This paper describes one approach to providing this research by presenting a sample student project.

INDIANA UNIVERSITY SOUTH BEND

Indiana University South Bend is the third largest of the Indiana University campuses. It serves approximately 7500 students from the greater South Bend area. The campus takes pride in instructional quality, and as components of the instructional infrastructure, has implemented programs that allow the undergraduate student to sample the research environment. Specifically, through two locally competitive programs -- Student/Mentor Academic Research Teams (SMART) and the IUSB Undergraduate Research Journal they have provided a realistic environment for research.

SMART

The Student/Mentor Academic Research Teams program provides, on a competitive basis, grants ranging from conference travel expenses to full summer fellowships for creative and scholarly activities. Here we describe the process and results for a summer fellowship. The eligibility requirements for proposal consideration are:

- Undergraduate IUSB student, beyond freshman level, 2.5 or greater GPA
- A faculty member who endorses the project and serves as mentor
- A completed application by the due date

In addition to these requirements, a completed report is required at the end of the fellowship, if awarded. All appropriate general grant guidelines, such as institutional review for human subjects, apply to the student as well.

A student who meets the eligibility requirements may then submit a proposal composed of:

- A cover page with name, address, project title, and other demographic data.
- A three to five page description of the project. While the faculty mentor may guide and critique, this document must be written by the student.
- Faculty mentor vita.
- Letter of support from the faculty mentor directly to the grants director assessing the feasibility, merit, student qualifications, expected effort, and educational benefits of the project to the student.

The proposal is then reviewed by an interdisciplinary research committee composed of both faculty and students.

IUSB UNDERGRADUATE RESEARCH JOURNAL

The goal, as stated on the web page [2], for the Undergraduate Research Journal is "...to promote research among undergraduate students at IUSB and to provide them with the experience of publication, providing contributing

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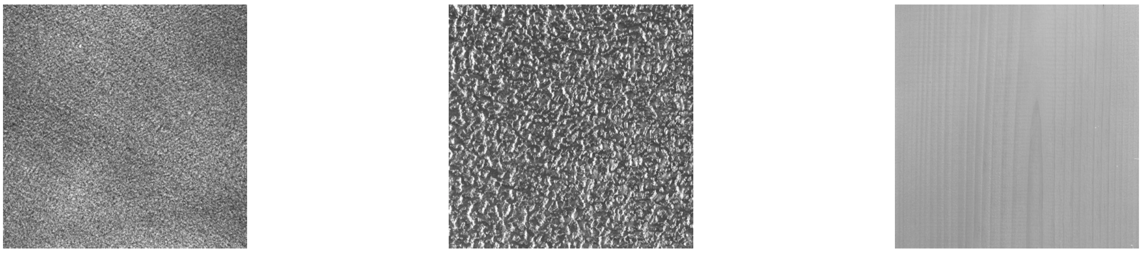

Texture *A (Fabric)* Texture *B (Metal)* Texture *C (Wood grain)*

Figure 1 – Images used in this experiment

students, referees, and the editorial staff with an introduction to the academic writing process." The call for papers, then, specifies:

- Papers must be written by IUSB undergraduates
- Only papers written within the past year are eligible.
- All papers are reviewed by a faculty member in the appropriate discipline.
- Any research involving human subjects must have institutional review board approval prior to conducting the research.

After submission the paper is reviewed by student referees recommended by their respective departments of expertise, and, upon acceptance, edited by students.

Each annual edition typically contains fifteen to twenty papers, and is approximately one-hundred pages in length.

SAMPLE STUDENT RESEARCH

Here we present an example of a typical student project. An expanded version appeared in the Undergraduate Research Journal [3]. Self-organizing maps, a type of neural network, are used to visualize abstract statistical vectors representing visual textures.

Visual texture, while an intuitive concept to grasp, is one that is difficult to rigorously define and quantify. Texture has been characterized as being made up of "repetitive patterns," [4] or possessing a "constant, slowly varying, or approximately periodic" set of local statistics. [5] Some examples of texture images are shown in Figure 1. Various techniques for analyzing texture data have been proposed and used with some success. These include geometrical, model-based, signal processing, and statistical methods.

Haralick [6] proposed a set of useful statistics derived from the gray level co-occurrence matrix. Among then are the Angular Second Moment, Contrast, Correlation, Inverse Difference Moment, Entropy, Variance, Cluster Prominence, Cluster Shade, and Diagonal Moment.

These statistics capture a wide range of the image's features. In practice, a set containing these nine statistics is computed for each image, and is represented as a nine-dimensional vector.

Visualizing these vectors, or image feature descriptors, was the primary goal of this project. Specifically, we explore the applications of Kohonen's self-organizing feature map as a visualization tool for these descriptors.

The concept of self-organizing maps of neural networks was first developed by Teuvo Kohonen [7]. It has found application in fields as diverse as the analysis of recorded human speech, the processing of images of the Earth taken from space, or the analysis of medical data. The basic SOM can be thought of as a sheet-like neural structure, in which each neuron contains a vector of the same dimensionality as the input data. The map is first initialized with random vectors, then "trained" by the following iterative process:

- An input vector, $\boldsymbol{x}$, is presented to the map.
- The map is searched for the component neuron containing the vector most similar to $\boldsymbol{x}$, as determined by a metric such as the Euclidian distance function.
- The closest vector, M_x, is located and modified to be incrementally closer to the vector $\boldsymbol{x}$.
- A neighborhood N_d about M_x is then defined as being all those neurons that are within distance d of M_x, and each neuron in that neighborhood is caused to become slightly more like $\boldsymbol{x}$ as the neighborhood radius d is decreased iteratively. Thus those neurons close to M_x become more like $\boldsymbol{x}$, but do so to a greater degree than those farther away.

Mathematically, the process is carried out as follows. Let t = 1, 2, … be the step index, and determine each best matching index c for each sample $x(t)$ by the following condition:

$$\forall i, \|x(t) - m_c(t)\| \le \|x(t) - m_i(t)\|$$

ASM	*Contrast*	*Correlation*	*IDM*	*Entropy*	*Variance*	*Diag. Moment*	*Cluster Shade*	*Cluster Prom.*
0.9684827	0.005723557	1.000000	0.9919758	0.6103299	.006407373	-0.0004233161	-8.991040e-05	3.377443e-05
0.03910838	0.8241672	2.457828e-05	0.1977914	0.9567972	0.8525648	0.8815748	0.7389579	0.6972131
0.03963804	0.8263306	2.675579e-05	0.1964169	0.9556544	0.8058157	0.8879519	0.6914841	0.6412812

Table 1 – Sample statistic vectors.

Following determination of this "winning" node $m_c(t)$, a subset of the nodes around it, determined by the "neighborhood function" $h_{c(x),i}$ are updated according to the following:

$$m_i(t+1) = m_i(t) + h_{c(x),i}(x(t) - m_i(t))$$

This regression is typically performed iteratively over available samples until a satisfactory map is formed.

Upon completion of this algorithm, we expect to find similar vectors, representing similar features, clustered close together in the final map. In general, we may view the SOM as a way of mapping a higher dimensional space to a lower dimension, while preserving much of the order inherent in the higher-dimensional structure.

VISUALIZATION OF BASELINE TEXTURES

For our initial experiment we chose textures available as part of the VisTex visual texture library [8]. We partitioned these textures into a training set and a testing set, selecting sample textures of each visual description (i.e. clouds, water, tile, etc). We then performed the following process on each set:

- Crop all images to a uniform size.
- Convert all images to a grayscale representation in the proper file format.
- Generate the nine GLCM statistics for each image, and place the resulting vectors in a data file – each line of the data file containing the nine vector components representing one texture.
- Normalize each column vector in the data file.
- Train the self-organizing map on the data.
- Display the map using a umatrix visualization. In a umatrix the map is represented as a grid of nodes. Each node is color-coded to represent the average distance between it and its neighbors, and labeled with the label of the input vector that it most closely matches (if there is one) or with a dot (if it matches no input vector).

The application of these steps is illustrated on the textures shown in Figure 1. Vectors, shown in Table 1, were generated from sub-images and used to train a self-organizing map consisting of 300 nodes arranged in a 30x10 hexagonal grid. Figure 2 shows the resulting u-matrix visualization. Note the clustering of the textures by visual similarity.

Following these initial experiments we expanded our study to include a wide variety of textures. Our goal was to see if the SOM segregated the statistical vectors in a manner that reflected the original image represented by the vector -e.g. do vectors representing similar visual images cluster together in the resulting display. To answer this question, we performed the following experiment:

- Generate three self-organizing maps of differing dimensions and parameters, but all with the training set as their input data.
- Map the testing set onto each of these maps.
- Evaluate the results by the following criterion: If the texture in the training set to which the training vector mapped the closest appeared visually similar, count the match as a success; otherwise, count it as a failure.

When evaluated over all the selected textures, the SOM typically mapped previously unseen textures in between 70% and 80% of the time. This is consistent with research literature, reporting the discrimination capability of the GLCM-derived statistics at about 80% on similar data sets [9].

VISUALIZING FINGERPRINT STATISTICS

Having explored the effectiveness of the self-organizing map algorithm for visualization of statistics derived gray level co-occurrence matrices on a baseline set of textures, we sought to explore its possible use in visualizing the texture statistics of human fingerprints. The fingerprint images we used for this experiment were acquired from the publicly available fingerprint image sample set on from the National Institute for Standards and Technology (NIST) [10].

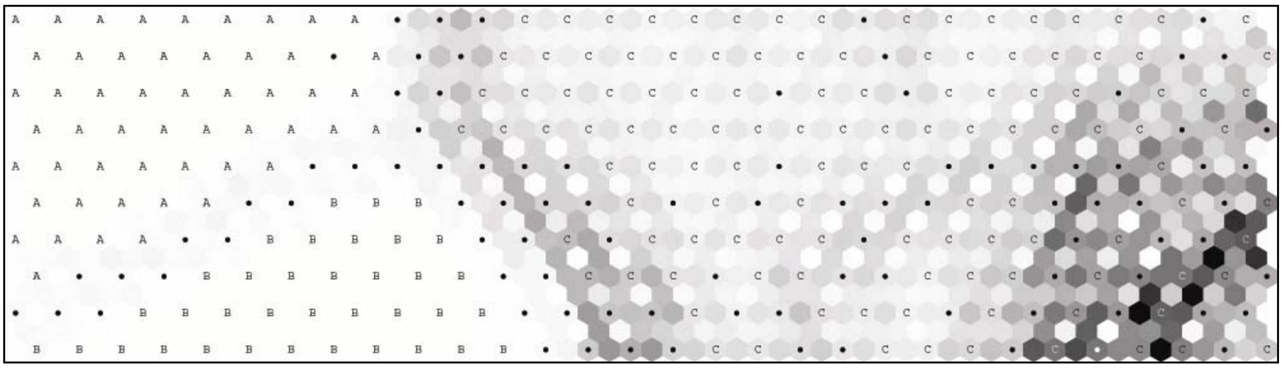

Figure 2 - Statistic vectors from three textures, A, B, and C, visualized using a self-organizing map. Note the clear demarcation between vectors.

Additional preprocessing was necessary during the preparation of these images to remove handwriting (where possible) and to form images of consistent size and orientation. Also, since these images were acquired under various lighting conditions, we performed histogram normalization on each image to standardize brightness and contrast. This involved modifying the histogram of each image through a Gaussian normalization process. After normalization was complete, we continued with the generation of the GLCM statistics. Figure 3 shows typical preprocessed fingerprints.

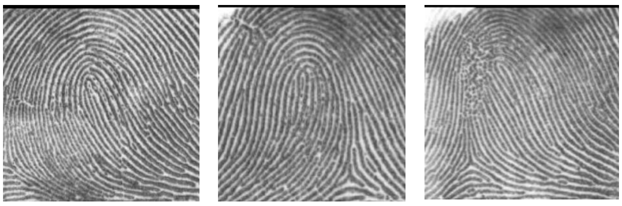

Figure 3 - The fingerprints from Figure 6, after preprocessing

The GLCM statistics were then used to explore the SOM algorithm's ability to discriminate the difference between vectors representing fingerprint textures and those representing the textures from the Vistex database.

Figure 4 shows one of the resulting maps, with fingerprint textures labeled "F" and all others labeled "T". Note that the vectors representing the fingerprint images are reasonably well separated from the other textures, evidence that the vectors representing their GLCM statistics are sufficiently distinct.

STUDENT CONCLUSION

We believe that self-organizing maps have value for visualizing GLCM texture descriptors. They show promise for both clustering and visualizing statistical vectors, encoding visual similarity, and recognition of textures not previously "seen" by the algorithm.

OBSERVATIONS

The infrastructure described in this paper has served students well, providing a realistic environment to experience every aspect of the academic research process from grant proposal to publication. This includes aspects often below the horizon such as the editorial coordination necessary to publish collected works.

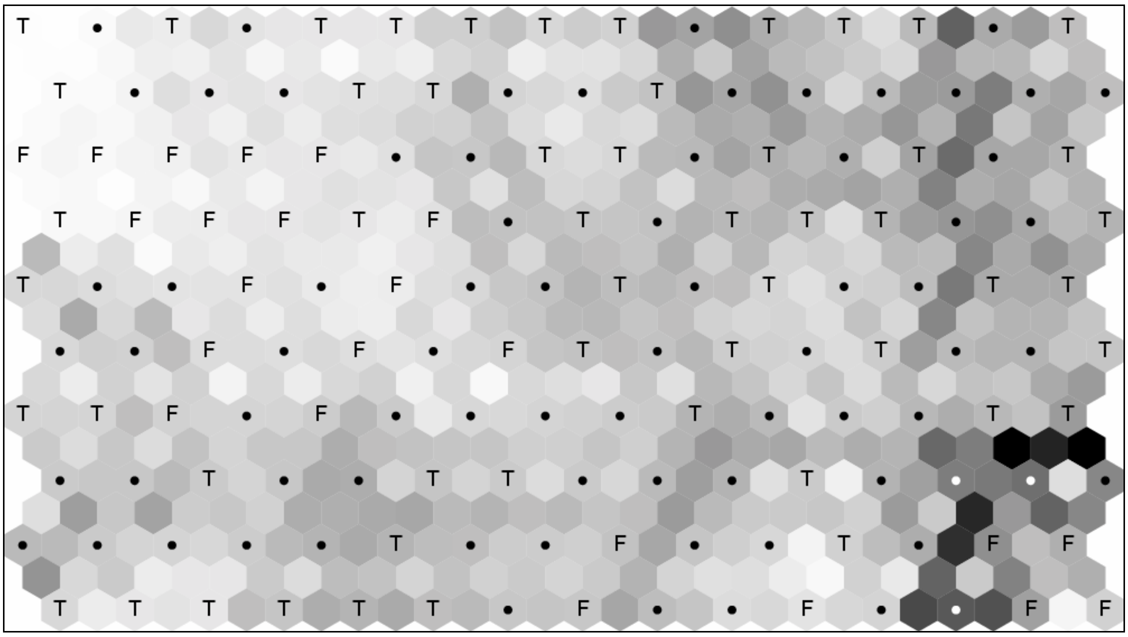

Figure 4 - Fingerprint and Baseline textures visualized

We believe that the process could be improved as well. Specifically, we believe that expanding the role of the Undergraduate Research Journal by allowing student submissions from other nearby colleges and universities would benefit our students by encouraging them to build contacts and relationships. It would also stand as a recruiting tool for potential graduate students by exposing them to the local research potential.

CONCLUSION

We believe that the potential for undergraduate participation in significant research projects is greatly enhanced by the funding and infrastructure provided by the university, and that it has the potential to be a positive influence beyond the university campus.

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