Lab 3

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# Introduction

The purpose of this lab is to apply classification techniques on images.

# Feature Analysis

## Initial Glance:

1. Looking at the texture images themselves on the SYDE372 homepage it is noted that some textures can be confused for other textures and vice versa. The textures are listed below:
   1. Raiffa can be mistaken for wood as the vertical stripes are as predominant in Raiffa as in the Wood texture
   2. Pigskin, Paper and Cork can be mistaken for each other as they all have a similar Stucco like pattern
   3. Grass and stone can be mistaken for each other as they have a similar pattern although grass has sharper distinctions between dark and light shades
   4. Cloth and Cotton and be mistaken for each other as they both have similar uniform features
2. The face texture is the most distinct as long as the whole face is viewed as there are many distinct features that must exist, such as the eyes and mouth, features that are highly unlikely to be found in the other textures in a similar pattern.

## 2x2 Block:

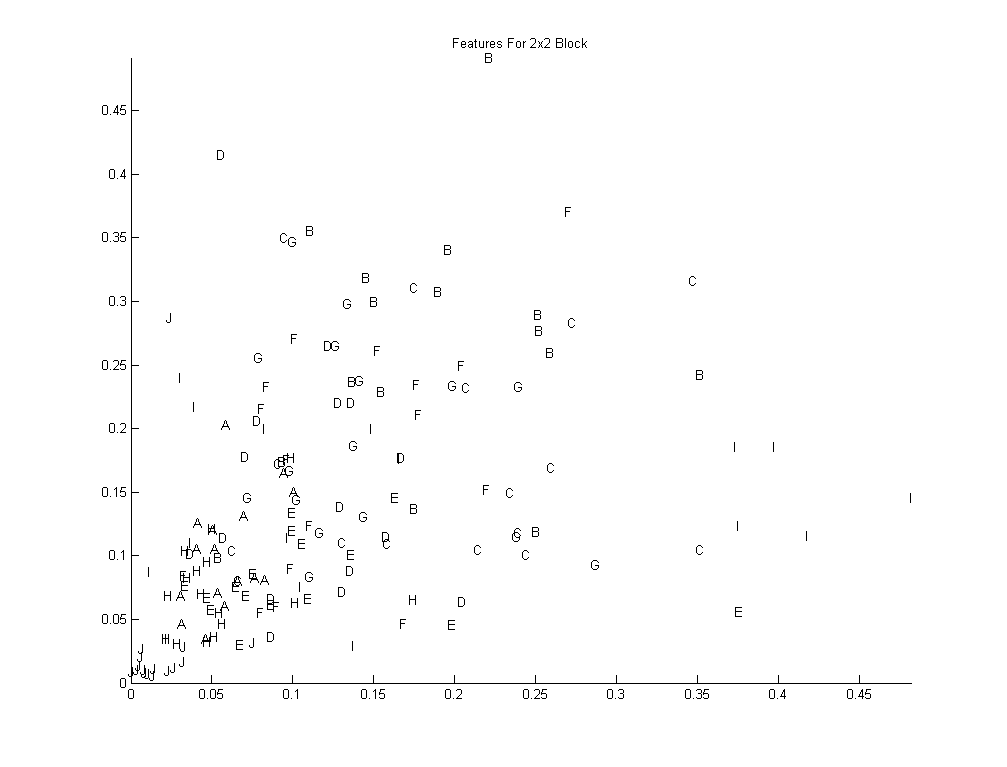


Figure 1: 2x2 Block Feature Plot

1. Looking at the feature data plotted above, it is noted that some textures can be confused for other textures and vice versa. The textures are listed below:
   1. Cloth (A), D,E, H
   2. B, C, F, G, I
   3. C, D
   4. D, F, G
   5. E, I
2. The face texture is the most distinct despite using a 2x2 feature block.

## 8x8 Block:

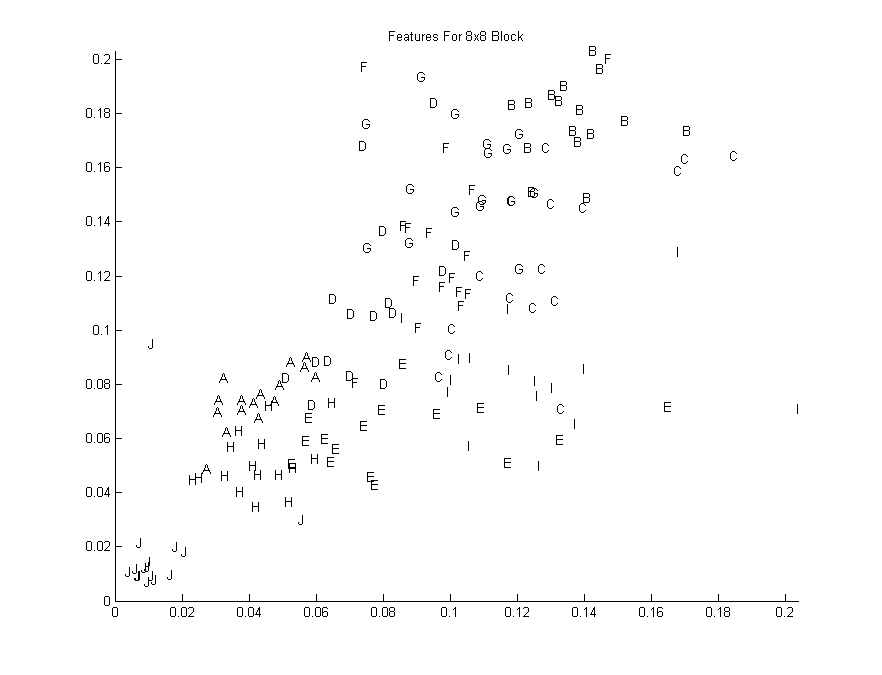


Figure 2: 8x8 Block Feature Plot

1. Looking at the feature data plotted above, it is noted that some textures can be confused for other textures and vice versa. The textures are listed below:
   1. Cloth (A),E, H
   2. B, C, F, G
   3. C, I
   4. D,E, F, G
   5. E, I
   6. F,I
2. The face texture is the most distinct using a 8x8 feature block.

## 32x32 Block:

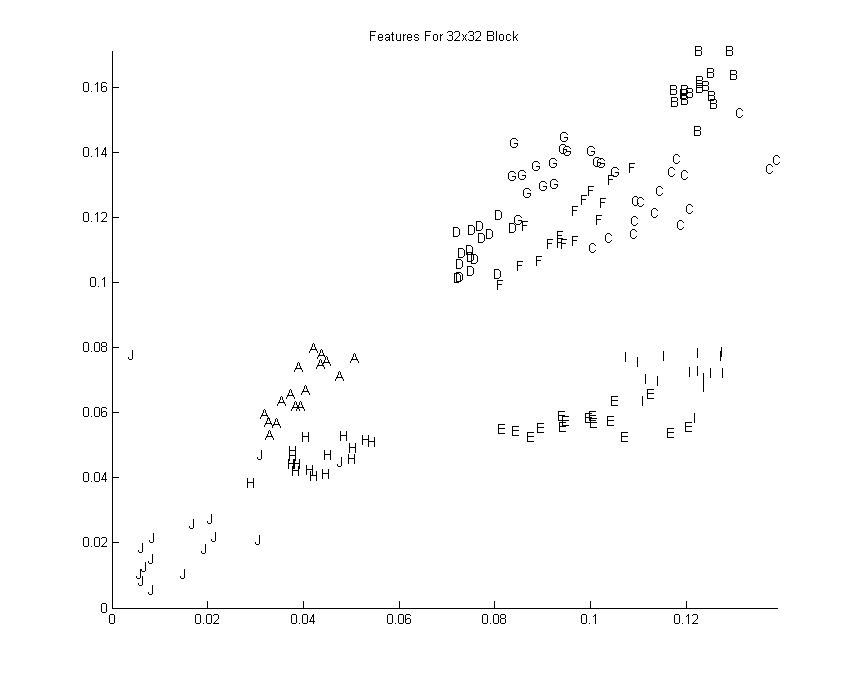


Figure 3: 32x32 Block Feature Plot

1. Looking at the feature data plotted above, it is noted that some textures can be confused for other textures and vice versa. The textures are listed below:
   1. C,F
   2. D,F,G
   3. E,I
2. The face texture is the most distinct using an 8x8 feature block.

# Labelled Classification

## 2x2 Block

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Truth | Classified | | | | | | | | | | Error |
|  | A | B | C | D | E | F | G | H | I | J |
| A | 3 | 0 | 0 | 1 | 4 | 1 | 0 | 5 | 2 | 0 | 81.25% |
| B | 0 | 6 | 1 | 2 | 0 | 3 | 3 | 0 | 1 | 0 | 62.50% |
| C | 0 | 1 | 1 | 2 | 2 | 2 | 7 | 0 | 1 | 0 | 93.75% |
| D | 2 | 2 | 3 | 2 | 1 | 4 | 0 | 2 | 0 | 0 | 87.50% |
| E | 2 | 2 | 0 | 1 | 4 | 1 | 1 | 1 | 4 | 0 | 75.00% |
| F | 1 | 1 | 1 | 2 | 1 | 5 | 3 | 1 | 1 | 0 | 68.75% |
| G | 0 | 3 | 1 | 2 | 1 | 3 | 4 | 0 | 2 | 0 | 75.00% |
| H | 2 | 0 | 0 | 3 | 5 | 1 | 0 | 5 | 0 | 0 | 68.75% |
| I | 0 | 1 | 3 | 2 | 2 | 3 | 4 | 0 | 1 | 0 | 93.75% |
| J | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 2 | 0 | 12 | 25.00% |
| Average Error | | | | | | | | | | | 73.12% |

## 8x8 Block

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Truth | Classified | | | | | | | | | | Error |
|  | A | B | C | D | E | F | G | H | I | J |
| A | 15 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 6.25% |
| B | 0 | 13 | 3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 18.75% |
| C | 0 | 2 | 4 | 0 | 1 | 5 | 0 | 0 | 4 | 0 | 75.00% |
| D | 1 | 0 | 1 | 9 | 0 | 1 | 3 | 0 | 1 | 0 | 43.75% |
| E | 2 | 0 | 0 | 0 | 8 | 0 | 0 | 3 | 3 | 0 | 50.00% |
| F | 0 | 0 | 4 | 5 | 0 | 3 | 4 | 0 | 0 | 0 | 81.25% |
| G | 0 | 2 | 4 | 0 | 0 | 3 | 7 | 0 | 0 | 0 | 56.25% |
| H | 3 | 0 | 0 | 0 | 0 | 0 | 0 | 13 | 0 | 0 | 18.75% |
| I | 0 | 0 | 1 | 1 | 7 | 2 | 0 | 0 | 5 | 0 | 68.75% |
| J | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 0 | 12 | 25.00% |
| Average Error | | | | | | | | | | | 44.37% |

## 

## 32x32 Block

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Truth | Classified | | | | | | | | | | Error |
|  | A | B | C | D | E | F | G | H | I | J |
| A | 16 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.00% |
| B | 0 | 16 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.00% |
| C | 0 | 0 | 8 | 0 | 0 | 8 | 0 | 0 | 0 | 0 | 50.00% |
| D | 0 | 0 | 0 | 16 | 0 | 0 | 0 | 0 | 0 | 0 | 0.00% |
| E | 0 | 0 | 0 | 0 | 16 | 0 | 0 | 0 | 0 | 0 | 0.00% |
| F | 0 | 0 | 1 | 0 | 0 | 14 | 1 | 0 | 0 | 0 | 12.50% |
| G | 0 | 0 | 0 | 0 | 0 | 3 | 13 | 0 | 0 | 0 | 18.75% |
| H | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 14 | 0 | 1 | 12.50% |
| I | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 15 | 0 | 6.25% |
| J | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 4 | 0 | 11 | 31.25% |
| Average Error | | | | | | | | | | | 13.13% |

Based on the numbers above it is clear as more information is added for each feature through an increase in sample image block size the easier it is for the MICD classifier to distinguish between each class when the training data is applied. As a result, there is a dramatic reduction in the average error rate, reducing by 60.68% when the change is from a 2x2 block to an 8x8 block and a reduction of 29.58% from an 8x8 block to a 32x32 block. It is noted that the remaining misclassifications for the 32x32 block only occurred among feature clusters that were very close to each other (figure 3). In this case between C, F, G, and between E & I, and between A, H, J. In order to reduce the error rate to 0% one would have to increase the sample block size until all clusters were well distinguishable from each other at least in the application for MICD.

# Image Classification and Segmentation

# Unlabeled Clustering