Classification of Pixel Data using a Support Vector Machine

Laura McCrackin, Alex Scigajlo, Jamie Turner
Electrical & Computer Engineering Department, McMaster University

January 31, 2013

Contents

1 Operational Information **3**
- 1.1 Class Masking 3
- 1.2 Point Generation and Pooling 3
- 1.3 Process Decision and Details 6

2 Choice of Parameters **7**
- 2.1 Testing & Results of Support Vector Classification 8

3 Classification of Testing Data **9**

4 Overall Effect **10**

5 Outcome **11**

List of Figures

1.1 Classification Mask used to determine class of training points 4
1.2 Mask relating desired point density to position 5
1.3 Colormap demonstrating point densities at different pixel locations 5

Chapter 1

Operational Information

1.1 Class Masking

To classify the picture as closely as possible to the desired result, it was necessary to review the details of the image for any features that could be extracted at an elementary level. The elementary level in this case is the raw image data available through individual pixel values. The support vector machine implementation in Matlab allowed for as many classification parameters to be passed for generating the classification structure.

When using the class mask, as seen in 1.1, it was necessary to generate a set of points to apply to the mask which maximized the positive effect on the support vector machine while reducing the requirement for an overly high number of required points.

As explained by Dr. Haykin, the support vector machine internally tries to maximize the distance between the points it is currently training against and the desired hyperplane(Haykin, 2008b). Randomly generating points from the entire images with no concern for position doesn't benefit the areas in the image where the distinction between both classes is quite complex.

1.2 Point Generation and Pooling

A method for promoting certain parts of the image while also allowing for automation of point generation is shown below. By applying a Gaussian blur filter to the previous hard-edged mask, a new mask where the point densities increase relative to the distance to the mask boundary is generated.

The training point generator works by sampling points through probability specified by the pixel values on this density mask. Visually the colormap,

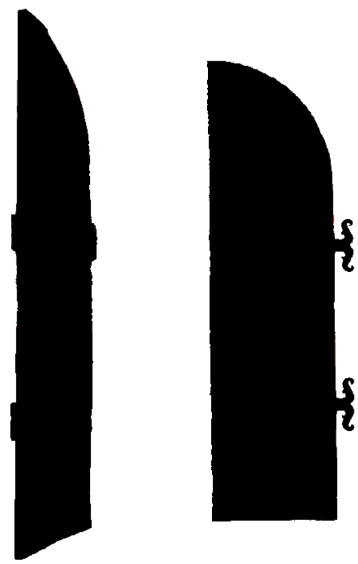

Figure 1.1: Classification Mask used to determine class of training points

as shown in 1.3, is an example in which the points will be more likely to be generated from. For small training sizes, there is no guarantee that points will exist from those levels in the produced training set as the pool itself is sampled and culled to bring forth the final training set.

Figure 1.2: Mask relating desired point density to position

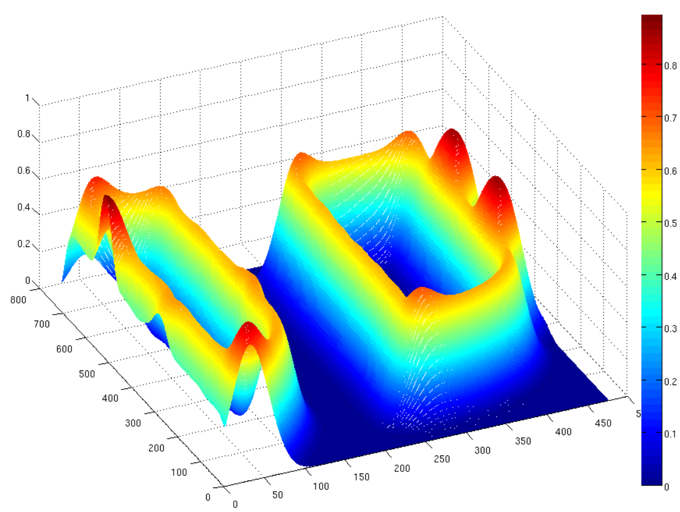

Figure 1.3: Colormap demonstrating point densities at different pixel locations

1.3 Process Decision and Details

Chapter 2

Choice of Parameters

When choosing the parameters to train the support vector machine, we decided to expand on the data available from the image. By applying certain filters to the image, it is possible to expand on the features of the image without requiring manual editing of the image.

2.1 Testing & Results of Support Vector Classification

Chapter 3

Classification of Testing Data

To determine optimal performance, we wanted to test the system setup with different numbers of training points.

Chapter 4

Overall Effect

Over the numerous types of parameters we could specify for the support vector machine to operate on, the order of effectiveness can be determined by the relative accuracy increase through its inclusion into the training data.

1. L*ab (Direct Pixel Value)

2. L*ab (Radial Blur Pixel Value)

3. XY (Pixel Location)

The pixel location had a surprisingly opposite reaction to the effectiveness of the system upon adding its values to the training data.

Chapter 5

Outcome

By limiting the data sent to the training set for the support vector machine, it was possible to maximize the

Bibliography

Haykin, S. (2008a). *Section 4.13 Cross-Validation*, pages 171–172. Prentice Hall.

Haykin, S. (2008b). *Section 6.1 Introduction*, pages 268–269. Prentice Hall.

Haykin, S. (2008c). *Section 6.2 Optimal Hyperplane for Linearly Separable Patterns*, pages 269–280. Prentice Hall.