Classification of Pixel Data using a Support Vector Machine

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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.

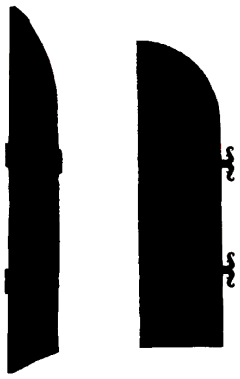

Figure 1.1: Classification Mask used to determine class of training points

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.

Figure 1.2: Mask relating desired point density to position

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

1.3 Kernel Function

For selecting the kernel to be used in the support vector machine, it was necessary to test those available to us from Matlab. The kernel functions available to us were as follows:

- Linear

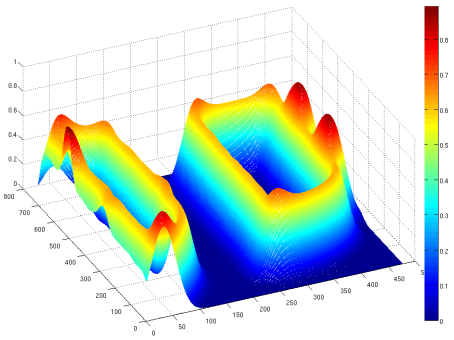

Figure 1.3: Colormap demonstrating point densities at different pixel locations

- Quadratic
- Polynomial
- Radial Basis Function (RBF)
- Multilayer Perceptron (MLP)

We decided to use the RBF kernel as it worked well in conjunction with the image processing done during training. To compare the kernels, we can examine the accuracy at sampling 1000 points from the image for training. When using the MLP kernel, we noticed the accuracy dropped over 40 percentile points for a similar calculation time to the RBF. Interestingly enough, the linear kernel function was not only faster than the RBF and MLP but also had a comparable accuracy to the RBF. The quadratic kernel function had a time almost halfway between the linear and RBF kernels.

1.4 Hyperplane Method

For the method of determining the appropriate hyperplane, we chose to use "Least Squares". The choices available to us were:

- Least Squares (LS)
- Quadratic Programming (QP)
- Sequential Minimal Optimization (SMO)

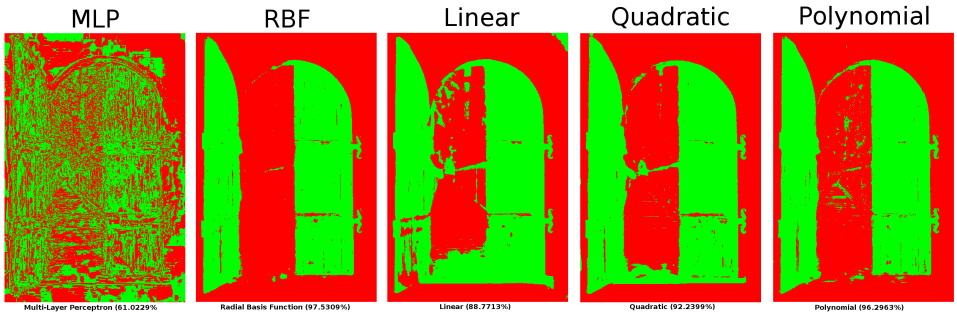

Figure 1.4: Comparison of the Different kernels using 1000 training points

Quadratic Programming was highly resource intensive for generating a classifier in respect to both Least Squares and Sequential Minimal Optimization. When using QP, Matlab failed to finish generating the hyperplane, thus we were unable to generate a classifier with the resources we had with QP. Due to this fact, we had to exclude it from our methods.

When comparing least squares versus sequential minimal optimization, there was no appreciable difference between the accuracies of the two. The differences between the images in 1.5 are very minimal, to the degree of the sixth significant digit or more.

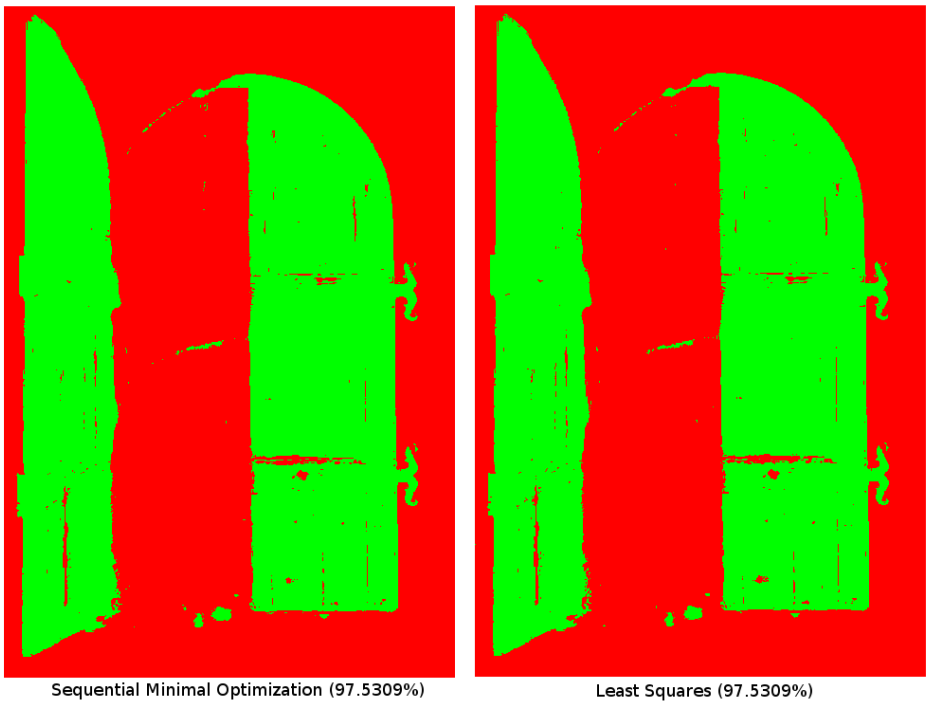

Figure 1.5: Comparison between methods of Least Squares and Sequential Minimal Optimization

Chapter 2

Process Decision and Details

2.1 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.

Chapter 3

Testing & Results of Support Vector Classification

3.1 Classification of Testing Data

To determine optimal performance, we wanted to test the system setup with different numbers of training points. Variable number of parameters were extracted from the image to test the improvement in performance of the SVM classification.

The testing data was gathered both before by hand, and automated for ease of testing. After gathering the points they were classified into their respective categories with a premade mask selecting whether specific points were part of the door or not.

3.2 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. The main parameters tested were as follows:

L*ab (Direct Pixel Value)

L*ab (Radial Blur Pixel Value)

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. Using only

(a) L*ab training (b) L*ab Radial Blur (c) XY Pixel Location

Figure 3.1: Results of Differing SVM information

the pixel coordinates to train the system had detrimental effects on the performance of the SVM.

Seen in the pictures, the hardest parts for the SVM to properly classify were the places with both similar colour and texture to the door. In these areas, the SVM had a higher probability to return false positive results.

3.3 Outcome

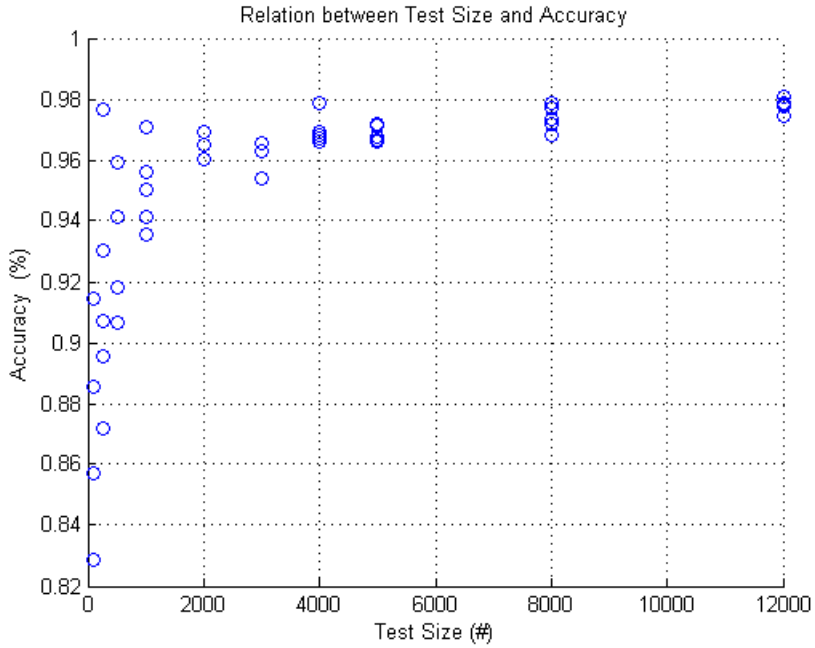

Figure 3.2: Changes in accuracy in the SVM from variance in the training set size.

By limiting the data sent to the training set for the support vector machine, it was possible to observe 90% and above performance for even small amounts of training data. The position of these training points had a greater effect on the results at when the total training points was lower. As expected, the results are very sensitive to the position of the training points – as more of the points will become support vectors that are further away from the optimal hyperplane. The sensitivity of the accuracy decreased drastically with increased number of point.

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.