1 Introduction

The Fourier transform is used to assess geometric characteristics of a particular spatial image domain. An image's representation in the Fourier domain is a representation the number of basis sine and cosine functions of varying frequencies which are present in the image. Because the image in the Fourier domain is decomposed into into its sinusouidal components, it is easy to examine the frequencies of the image and their geometric relation.

This report explains my process of classification of text based on features of the image extracted from the Fourier domain.

2 Approach to analysis in the Fourier domain

To start with, I superimposed the magnitude spectrums of the training data to produce three graphs which illustrate the geometric characteristics of the letters in the Fourier space. Over the top I have illustrated the regions of the chosen features by blue lines, the feature selection process is detailed in section 3

Figure 1: Fourier transform of T characters

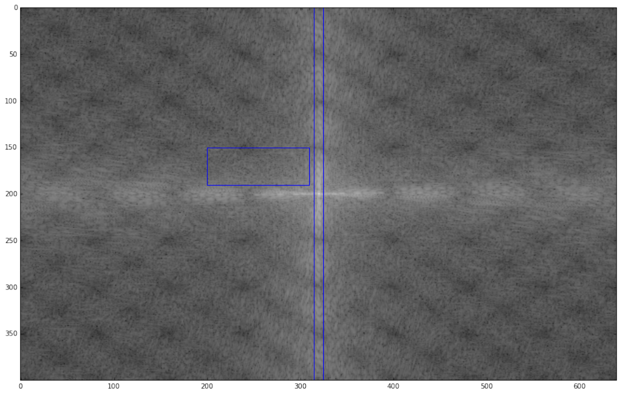


Figure 2: Fourier transform of S characters

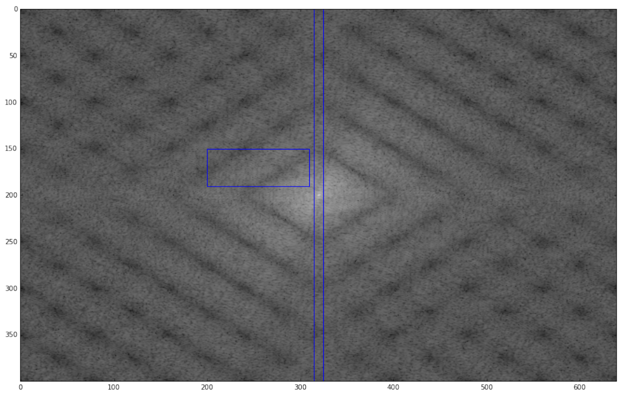
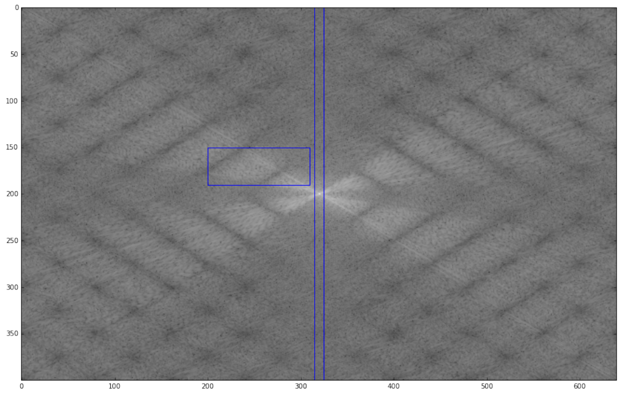


Figure 3: Fourier transform of V characters



Considering the three Fourier images

- Figure 1 shows the general fourier space for the character T, from the image we can observe that the power spectrum has high magnitude along the vertical bar passing through the centre, this corresponds to the line which forms the top of a character T. Similarly, there is another high magnitude bar passing horizontally through the centre, corresponding to the vertical part of the character

- Figure 2 shows the general fourier space for the character S, the power spectrum for S shows only small magnitudes for directions in exclusively the horizontal or vertical direction, this corresponds to the fact that a regular character S does not change in only the vertical or horizontal directions. As seen, the highest magnitudes lie relatively evenly distributed within the central diamond region, illustrative of change in both the horizontal and vertical directions, at varying angles. It is also just visible with the naked eye that there is a slightly more intense band in the $u = v$ line of the fourier space, this corresponds to the almost diagonal line which is part of some of the S test characters

- Figure 3 shows the general fourier space for the character V, the power spectrum shows two distinct bands in the lines $u = v$ and $u = -v$, these correspond to the two diagonal lines which form the letter V. We can also see the magnitude along vertical line passing through the centre is very low, the corresponds to the fact that there is very little change purely in the horizontal direction for the character V, eg the only point at which exclusively horizontal change is likely to occur is at the bottom of the character

3 Feature extraction

The characters are classified into three seperate classes using two features, each feature is designed to positvely identify one character, the third character is indentified by logical deduction. The features are obtained by taking the sum of the square of the magnitude in specific regions as shown in figures 1 to 3.

the first feature I picked was a narrow vertical rectangle passing through the centre and spanning the height of the image, I reasoned that the rectangle would measure change only in the horizontal direction of a image, consequently this feature should produce the highest value for for T, with a lower value for S, as S contains some horizontal information in the top and bottom parts of the character, and the lowest magnitude for V, as there is only a very small area at the bottom in which the change is purely horizontal.

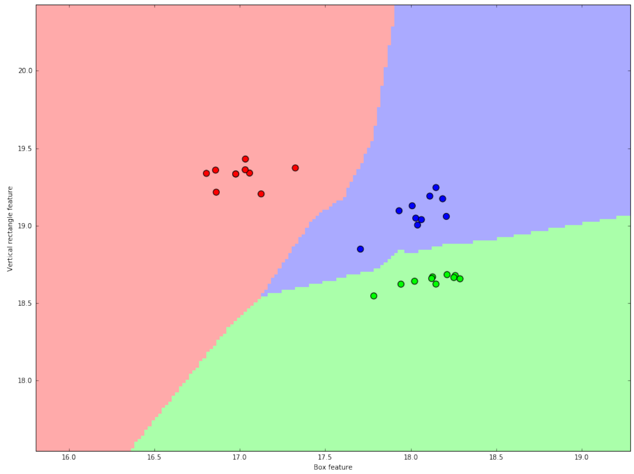
The second feature chosen was a rectangular box in the top left quadrant of the image as shown, this area is aimed at positively identifying the character V. I reasoned that this feature should have the highest value for this character owing to the fact that the character V changes most in both the horizontal and vertical directions.

4 Results of Fourier Domain analysis and analysis of the classifier

Using the features chosen in the previous section, I computed the sum of the power spectrum in the regions selected by the features for each letter. I then applied the nearest neighbour procedure with $k = 1$ and uniform weighting to the list of values produced by the feature extraction, the results are shown in figure 4. The figure shows the decision regions for the nearest neighbour classification given a test point, the red region shows the area where a point will be classified as a T, the blue region shows where a point will be classified as a S, and the green area shows where a point will be classified as a V.

The training data produced three regions which correspond to the letters T, V and S. The clustering seems satisfactory, except for one of the S points. Observing figure 4 we can see that one S value is far closer to the V decision boundary than the rest. I reasoned that the shift towards the V decision boundary must relate to a test character which had lower overall magnitude in the center vertical line of its Fourier space. Further this character would have a lower magnitude

Figure 4: Result of feature extraction, with decision boundaries shown



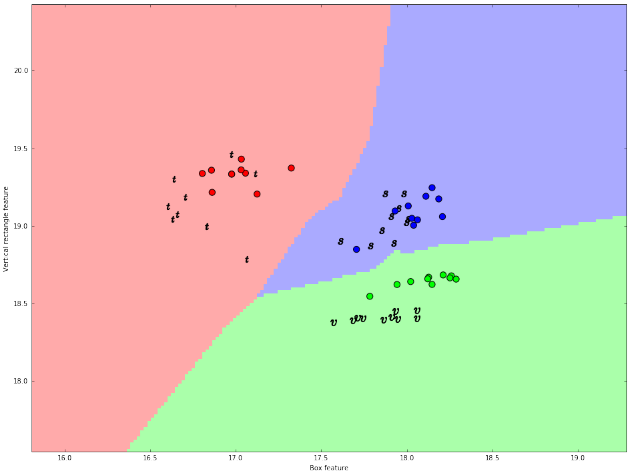
in diagonal lines of its Fourier space. One by one I removed datapoints from the dataset and plotted the resulting nearest neighbour classification, I found that the point to be **S7**. The lines forming S7 were thicker than all the other test Ss, furthermore, it was more curved at its top and bottom. As the top and bottom of the S were not as straight as the others, their respective magnitudes as computed by the vertical rectangle feature was lower, hence why it is shifted towards the S/V decision boundary.

To test my classifier, I created 10 new images for each character. The figure 5 shows the resulting classification for the points. Observing the graph we can see that all input Ts have been classified correctly, each T also lies relatively far way from the decision boundary between T and S. Considering the next character, Ss have all also been classified correctly for my test data, some of the Ss are near the S/V decision boundary, this corresponds to a test S which had a particularly diagonal middle section. My classifier classifier also correctly identified all test V characters.

Next, I wanted to see how the classifier would cope with extreme cases for some test characters. I created the characters seen, the characters seen have been drawn to any weaknesses in the chosen features. Figure 6 illustrates the resulting classification for these points

figure 6 shows the resulting assignment of the characters seen above. Referring first to the Ss, observing the figure we can see that the first two Ss have been classified correctly despite the fact that both contain areas of exclusive horizontal change, the small amount of curvature was enough to distinguish them from Ts. The third

Figure 5: Result of feature extraction, with test data points shown



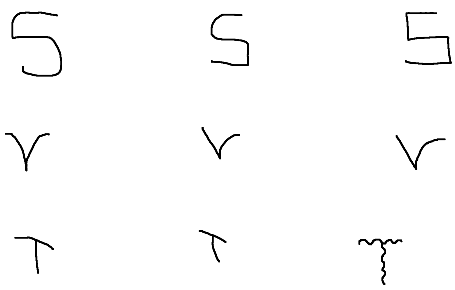
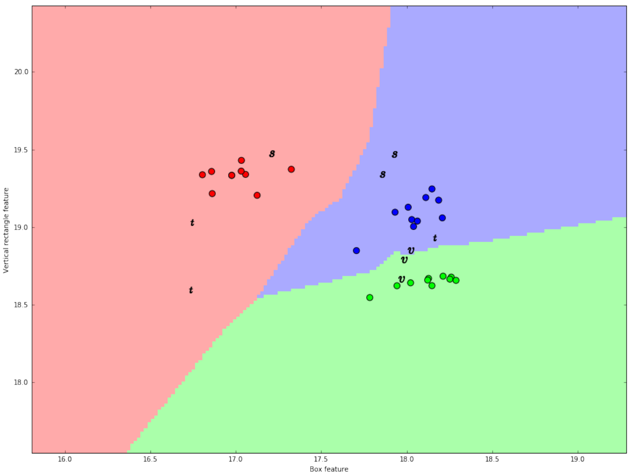


Figure 6: Assignment of extreme test characters



S, however, has areas almost *only* containing exclusive horizontal or vertical change, leading to its classification as a T

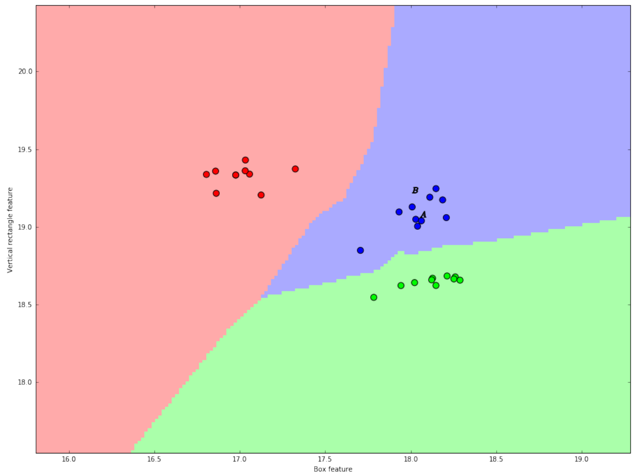
Considering the Ts, observing the figure we can see that two of them have been correctly classified as Ts, the points lie further away from the training cluster due to the fact that the Ts drawn have a much smaller horizontal component as a whole. The T composed of wiggly lines has been classifed as an S owing to its change magnitude in many directions.

Lastly considering the Vs, we can see from the figure that again two of them have been correctly classified, they lie very close to the boundary because they contain enough horizontal change to push them in the direction of T by the vertical box feature. This argument applies to why the third v is incorrectly classified as an S - the box classifier identifies it as a V, but because of the presence of the horizontal line, it is shifted by the first feature in the T direction, hence it is classified as an S.

5 Classification of A and B

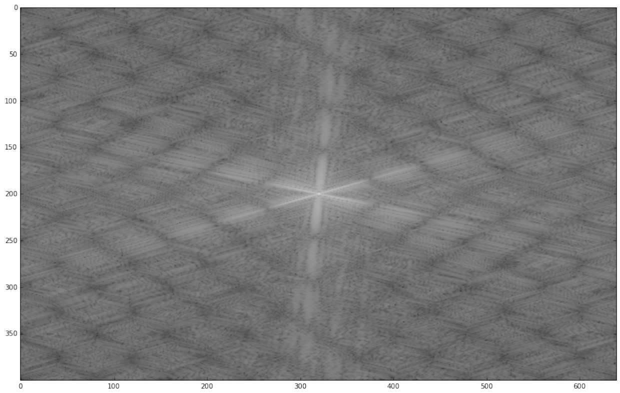
Figure 6 shows the classification of the characters A and B, as seen both lie near the centre of the S decision area, hence both have been classified as Ss. This can be explained by examining their Fourier spaces.

Figure 7: Classification of A and B



Why is A classified as an S? We can see why A has been classified this way if we examine the classification feature by feature. Firstly, considering the box feature: A lies almost directly in the centre of the V cluster with respect to the box feature axis. This can be explained by the diagonals seen in the fourier space of the letter A as seen in figure 8 - these cause the box feature to classify the character as a V. Secondly, examining the classification based on the vertical rectangle feature: the vertical rectangle feature is sensitive to horizontal change. Again examining the Fourier space of the A, we can see a line of high magnitude running almost through the centre, this corresponds the the horizontal part of the character A. Hence because of this component, the vertical rectangle feature classifies this as a T. So, overall the A is classified as an s because of the combination of these two features.

Figure 8: Fourier space of A



Why is a B classified as an S? Again examining the result feature by feature. Considering the box feature: A lies in the region of the V cluster with respect to the box feature axis. This can also be explained by the diagonal lines $u = v$ and $u = -v$ in Fourier space of B as seen in figure 9. These have lower magnitude than the letter A, and as a result have a lower value in the box feature axis. Secondly, examining the classification based on the vertical rectangle feature: the vertical rectangle feature is sensitive to horizontal change. Examining the Fourier space for B, we can see a vertical line of relatively high magnitude running through the center, this corresponds to the three horizontal sections partly composing the character B. As a result of this, the vertical rectangle feature classifies this as a T. Therefore, similarly to A - because of the combination of the fact that the B is classified as a T by the vertical rectangle feature, and as a V by the box feature, the result is the the B is also classified as an S.

Figure 9: Fourier space of B