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 hence influencing the geometric structure in the spatial domain. This report explains my process of classification of text based of 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.

Figure 1: Fourier transform of T characters

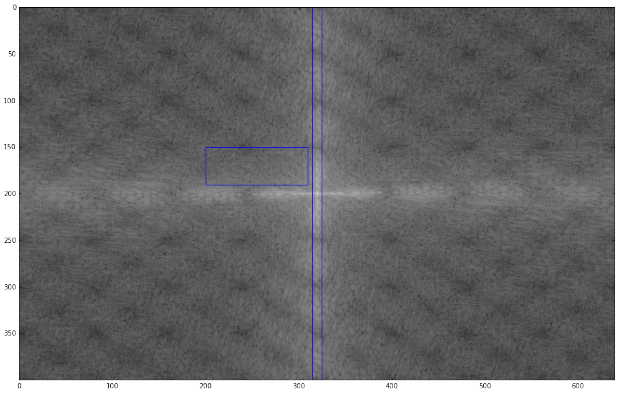


Figure 2: Fourier transform of S characters

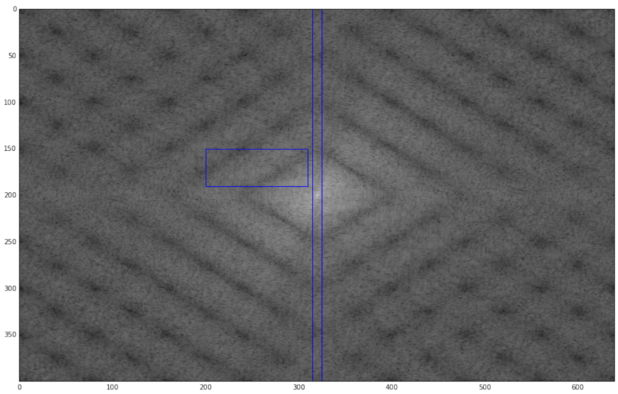
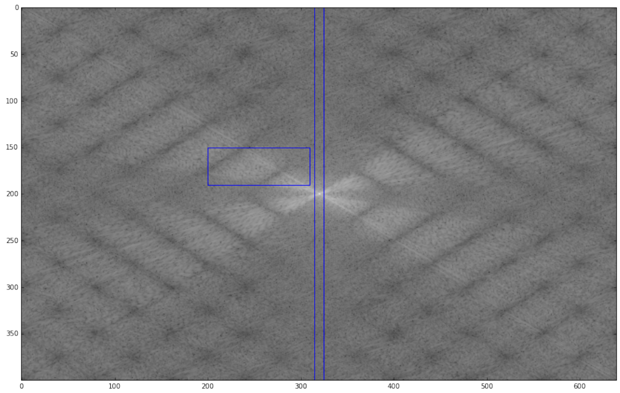


Figure 3: Fourier transform of V characters



Considering the three Fourier images

- Figure 1 shows the average 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 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 average 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 $y = x$ 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 average fourier space for the character V, the power spectrum shows two distinct bands in the lines $y = x$ and $y = -x$, the 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 Choice of features

When picking features for the use of classifaction, the aim is to use regions of the fourier space which differ the most between fourier spaces for the given images.

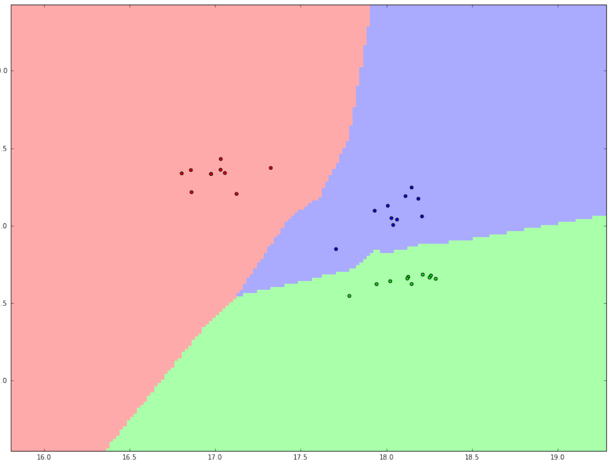
Leading on from the explanation of the fourier representation of the characters, the first feature I picked was a narrow vertical rectangle passing through the centre and spanning the height of the images, I reasoned that: The rectanlge would measure change in the horizontal direction of a image, consequently - the overall magnitude spectrum within this region is largest for the letter T. Furthermore, we can observe that the amount of horizontal change is next largest in the S character(owing to the top and bottom near horizontal lines which are components of the S character), the smallest amount of horizontal change can be seen in the V character, 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, I reasoned that I should use a feature which did not include change in the vertical or horizontal directly exclusively. I reasoned that the T would have the lowest power magnitude in the region mentioned, owing to the fact that a T is composed of a vertical and horizontal line placed orthogonally to one another. The next highest magnitude should be that of the S, as seen from the Fourier space, S has a high magnitude in the central diamond region. V should have the highest magnitude owing to the fact it changes the most in both the horizontal and vertical directions

4 Results of Fourier Domain analysis and analysis of the classifier

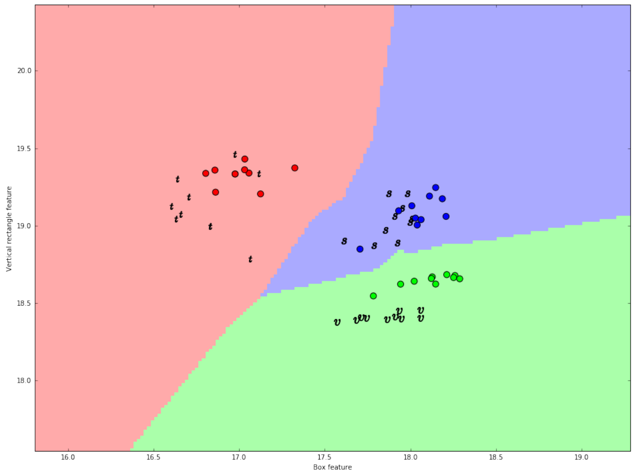
Using the features chosen in the previous section, I computed the sum of the power spectrum in the regions selected by the features for each letter. I then applied the nearest neighbour procedure with $k = 1$ and uniform weighting to the list of values produced by the feature extraction, the results are shown in *fig. 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.

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



The training data produced three regions which correspond to the letters T, V and S. The clustering seems relatively good, except for one of the S points. Observing fig 4 we can see that one S value is far closer to the V decision boundary than the rest. I reasoned that the culprit would be an S which had more diagonal information in it than the others, the increased intensity in the $y = -x$ line in the fourier space would cause it to increasingly resemble a V. One by one I removed datapoints from the dataset and plotted the resulting nearest neighbour classification, I found that the culprit was **S7**. *picture of S7 vs superimposed images of others*

To test my classifier, I created 10 new images for each character. The graph below 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 near the decision boundary for Ss and Ts, this corresponds to the more horizontal tops and bottoms of some of the test Ss. my classifier classifier also correctly identified all test V characters, however one of test Vs was very close to the decision boundary between S and V, this is a consequence of that particular V being extremly curved.



Next, I wanted to see how the classifier would cope with extreme cases for some test characters. I created the characters seen below, the characters seen have been drawn to any weaknesses in the chosen features

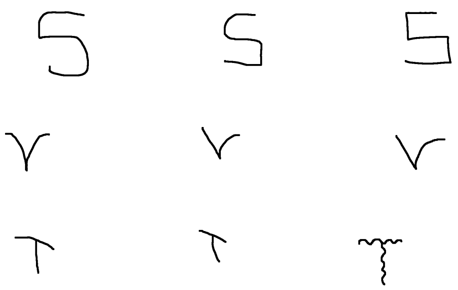


Figure 5: Assignment of extreme test characters

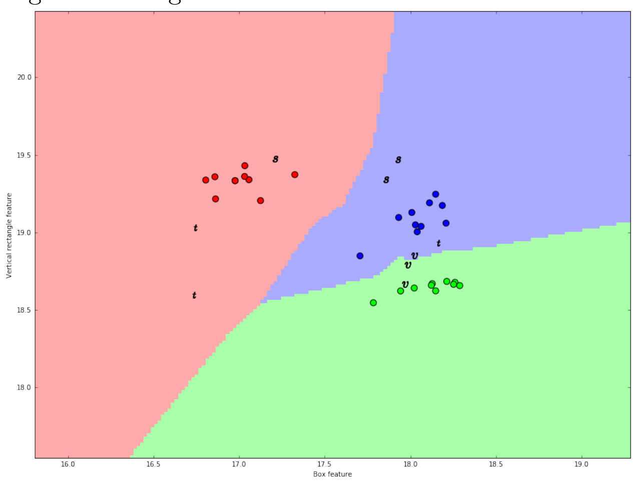


fig 5 shows the resulting assignment of the characters seen above. Referring first to the Ss, observing the figure we can see that the first two Ss have been classified correctly despite the fact that both contain areas of exclusive horizontal change, the small amount of curvature was enough to distinguish them from Ts. The third T, however, has areas almonst *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.

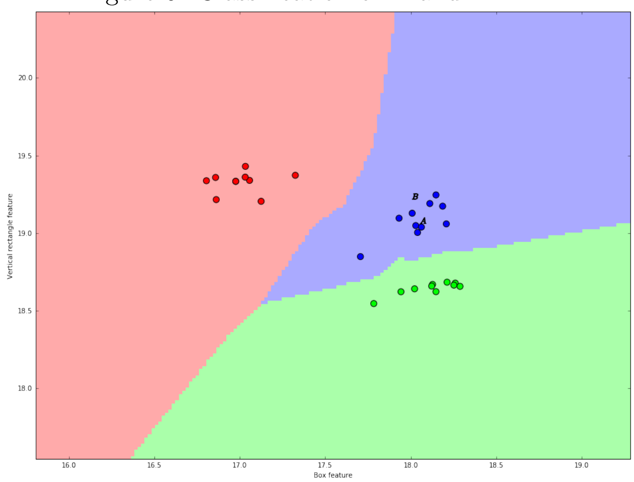
Lastly considering the Vs, we can see from the figure that again two of them have been correctly classified, they lie very close to the boundary due because they contain enough horizontal change to push them in the direction of T by the first feature. This argument applies to why the third v is incorrectly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

5 Decision region plots and their angles

6 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 6: Classification of A and B



Why is A classified as an S? It is easy to 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 relation to the box feature axis. This can be explained by the diagonals seen in the fourier space of the letter A - 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 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 7: Fourier space of A

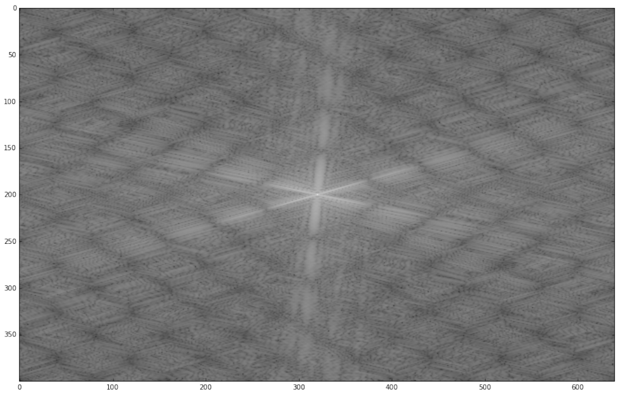


Figure 8: Fourier space of B