Symbols,Patterns, Signals CW2 Report

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1 Analysis of the fourier space

The fourier transform of an image can produce a magnitude and phase spectrum which can be used as an analysis tool. While the phase spectrum is just as important as the magnitude, the latter has far greater significance in this coursework. As shown in fig.1, the magnitude spectrum, also known as the fourier space, contains geometric information from different classes. The centre region of the fourier space is represented as a low frequency area, while the outer area as a high frequency area. From left to right, fig.1 shows the average Fourier space of 10 images of character ”T”,’V’ and ”S” as a training data.

The Fourier space of the character “T” is the easiest to identify among all three characters, as it contains a horizontal and vertical line which also shows in the pattern of its fourier space. The character “V” is made of two line with an 30 degree angle separation. As a result, its fourier space is consist of a flat “x” shape. The character “S” has a curve shape. Due to its feature of changing frequency in different direction, It has a texture pattern in the fourier space.

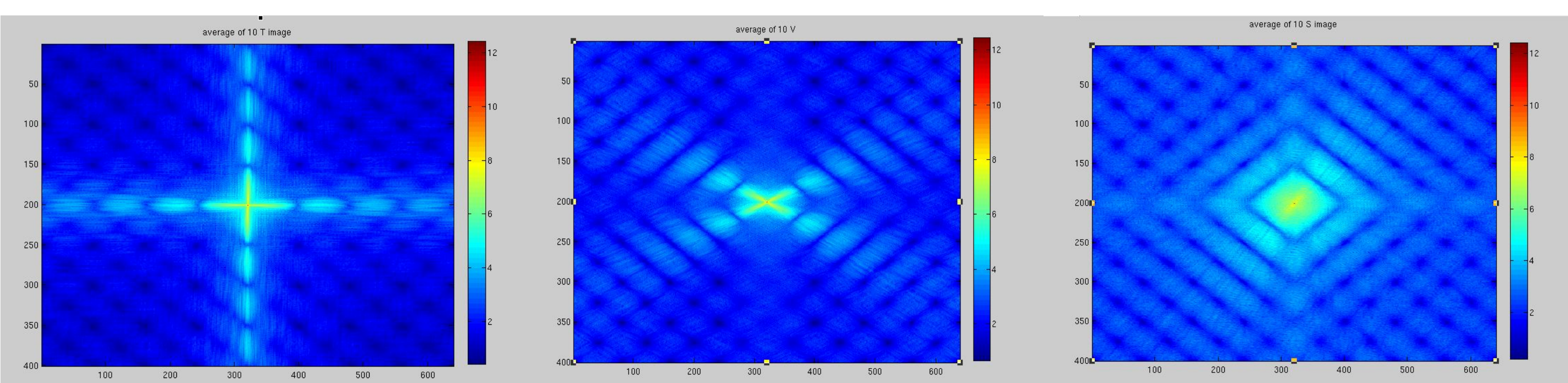


Figure 1

2. Feature Selection and Feature Extraction

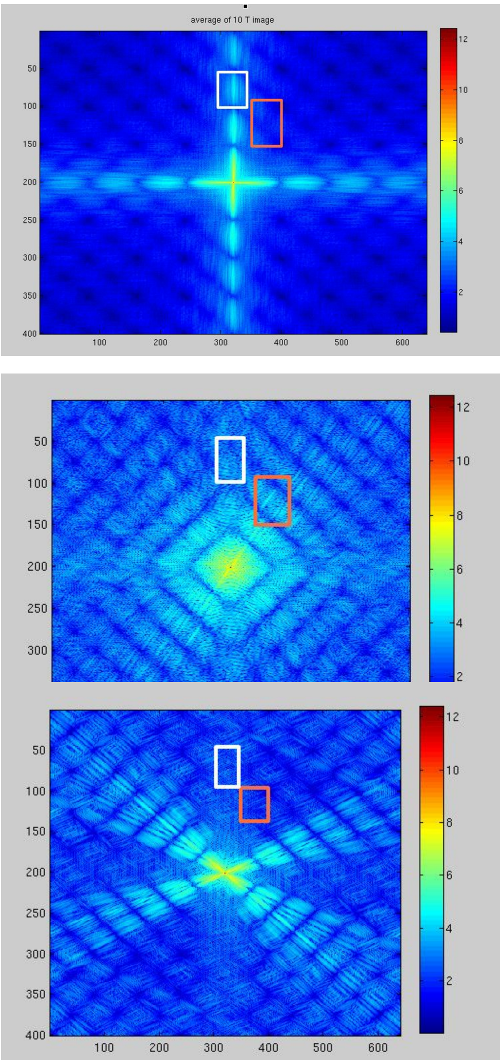


Figure 2

In this coursework, the features are selected to represent the character regardless of its size, font, position or rotation. According to the observation and analysis from the fourier space, common features are collected for different characters.

1) The first feature is in the middle center of the image, identified as a white square. Brightness in this area in the Character T reflects a high magnitude value. Character S however, has a smaller value with a sparse look and an even distribution throughout the region. Character V, regardless of different ways of writing, remains the lowest magnitude value in this region.

2) The second feature is shown with an orange rectangle located next to the first feature on the top right of the fourier space. Character T has almost none in the second region. Character S has the highest value, due to its texture pattern. Character V shows no significant value compared with Character S.

Two features is enough to separate the three classes. However, a high dimension of data in the selected region is hard to manipulate and analyse for classification.Thus, the feature extraction technique is employed to reduce the dimension of the matrix and used for further classification.

In this coursework, the feature extraction technique used is to power sum all the values in the matrix.When this is calculated, the one with higher density in the region will have a much higher sum. This can effectively separate the class from the one with a lower density. Feature 1 can properly single out character T from V and S, while feature 2 single out character S. As shown in the fig. 3, three classes are well separated and well clustered.

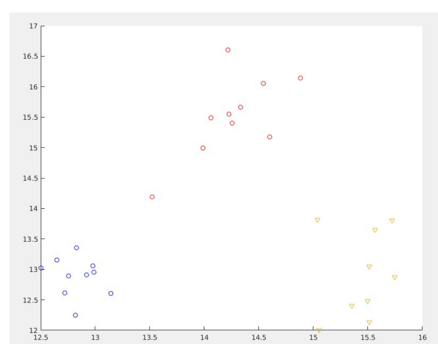


Figure 3

3. K-nearest neighbors classifier

In order to verify the reliability of the feature selected, K near-neighbour has been applied to the training data. Different numbers of neighbour(k value) has similar result in this context. In Fig 5,this number is set to be 3. The decision regions are obtained by creating a mesh grid and applying the KNN algorithm afterward.

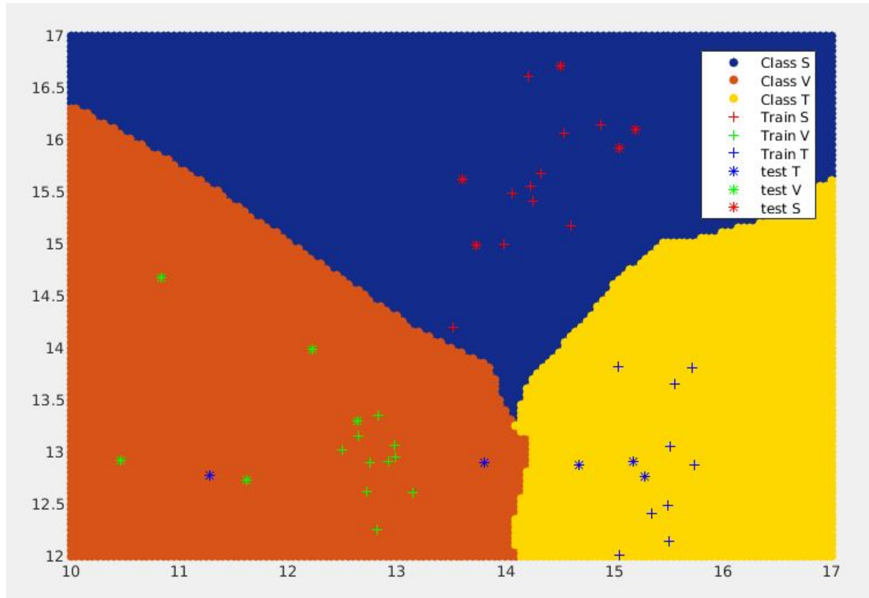


Figure 5

V has a low value in both feature, situated at the left region in the figure. T and S has similar value in the first feature sharing the same value along x-axis, while S has a high value in the second feature shown in the top right region.

4. Test data

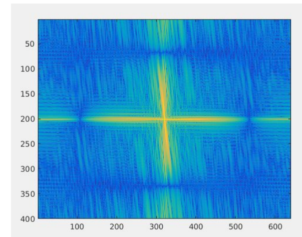
To test the selected features, 15 test datas are generated for the three classes, with each class having 5 different categories of images, namely normal, very large, translated, italic,and small. 13/15 are classified to be in the correct class. Only two images of T are misclassified to be V. This is corresponding to the test3.gif and test4.gif of fig.6. Refer them to be *P1,P2* .

Figure 6

5. Analysis test data

Plotting *P1* , *P2* in the fourier space gives us a more profound understanding of the problem. The first image has a missing area in the vertical line, which caused the data to have a lower x-axis value and thus be identified to be V.The translation of the T has no effect on the shape of the fourier space, and so the image still retains a vertical and horizontal line.

The second image indicates an italic T. The rotation feature of its spatial domain reflects in the rotation in the fourier space. This affects the value in the first feature, which relied on the vertical property of T. In the end, the fourier space looks similar to V with a larger angle between two segment lines.



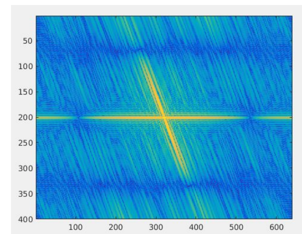
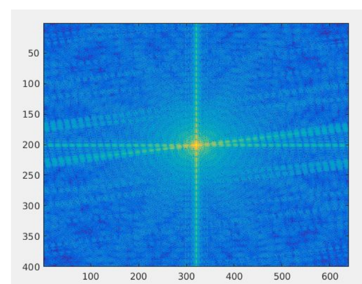
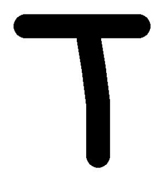


Figure 7

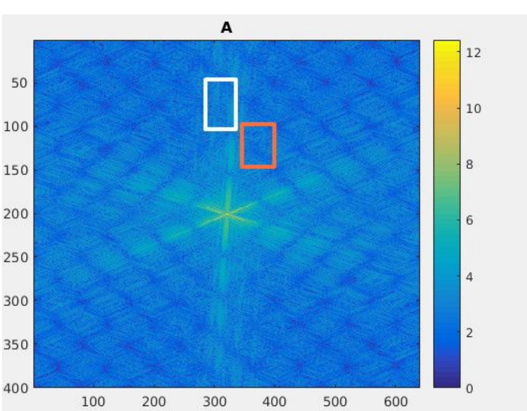
With further analysis on T, an additional experiment was carried out by plotting a T with larger thickness. The fourier space has more consistent value along the vertical line. A hypothesis is drawn that the thickness of the writing has a small impact on the outcome of the classification. In *P1 and P2* the T is drawn using a thin pen. This has a higher likelihood in change of frequency in the fourier domain.



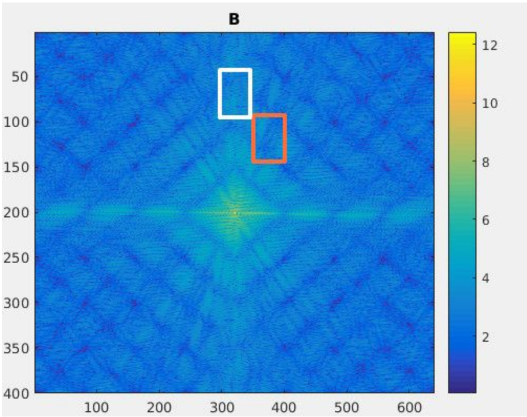


To conclude, the classifier works well in all character trials, with only exception on the italic T. According to the property of fourier space, it is a conjugate symmetric image. So if the character has been rotated 180 degree, it will have the same fourier domain. The italic T looks similar to a V when applying the 180 degree rotation, which in the end has a similar fourier domain and caused it to be misclassified as character V.

6. Analysis of A and B character



To classify character A and B using the classifier, the first step is to plot both of the characters into fourier domain and observer what they have in common. The Magnitude spectrum of A is similar to combination of V and T, with a 30 degree angle between the two line segments and one vertical line. Features



of B are similar to S sharing a texture pattern with additional horizontal line.

Plotting the features in the decision region, the test point of A is lying in the region of T,in fig.8. According to the selected feature, A has high density in first feature, and low in the second. It has been correctly classified as character T.

The test point of B has high density in both features, thus classifying as an S on the top right region of the kNN decision region.

7. Alternative classifier

An alternative classifier named nearest Centroid (NC) classifier has used as a comparator to the previous classifier. NC algorithm will classify the test point to the class whose mean is closest to it. It works the same as considering only the mean of the training class and applying knn classifier with k=1. The boundary therefore tends to be a straight line. The use of kNN and Nc has the same classification result. However, as clearly shown in the graph of NC classifier, there is an one red data lying on the boundary of the two regions. Compared with the kNN decision region, the boundary is much smoother and goes around this red data point. All training and test data as well as the A B data are classified to be the same between these two methods.

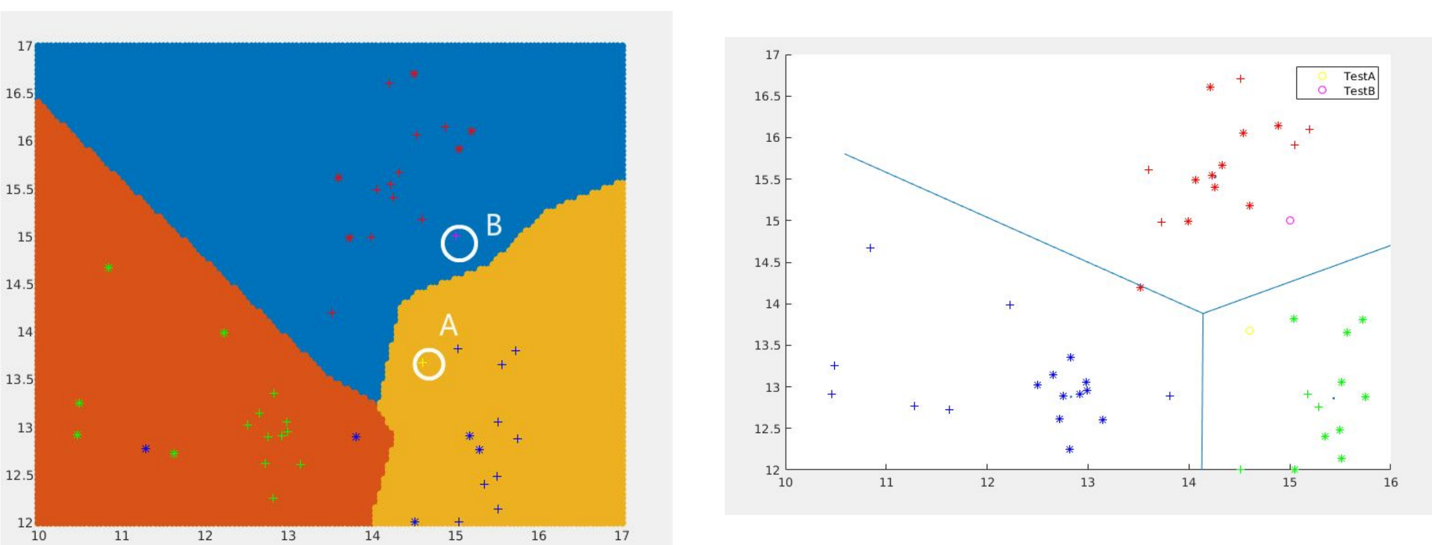


Figure 8 kNN Decision Boundary vs NC classifier

8. Conclusion

In this coursework, two methods of classification are chosen to meet the requirements. kNN classifier has produced a better outcome and has a smoother boundary compared with NC classifier. However, the well formed clusterings selected from two features extracted using power sum are not easily affected by way of classifications. In both cases, All the data remains in the same classification group.

9. References

[1] Mirmehdi, M. (2016). [online] Available at: https://www.cs.bris.ac.uk/Teaching/Resources/COMS21202/MM/2016/04FeaturesSlides.pdf [Accessed 28 Apr. 2016].