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Assignment 1: Counting Objects In Images

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Contents

1 The Problem

Show how the objects in an image can be automatically counted in an image to enable decisions based on the number of certain objects in an image. The problem suggests we perform an object based classification on an image. I have chosen to classify an image of different coloured balloons in the sky. See figure 1 below.
The softwares used to perform the object based classification is the eCognition Developer Trial and ArcMap.

Figure 1: Original Image

2 Methodology

2.1 Pre-processing

The image has shadows and a lot of the balloons have variations in their colour due to them reflecting the light. Layer mixing to help distinguish between the objects is useful due to these variations in light and colour intensities. This was especially useful in distinguishing the blue balloons from the blue sky. I performed the layer mixing using varied weights on the RGB image. See figure 2.1.1 below.

Figure 2.1.1 Layer Mixed Image

A segmentation is then performed on the image. The aggregation of the pixels is based on the roundness (for shape) and compactness of the objects in the image. I chose to use a scale parameter of 35 as I found this the best to segment portions where there are many balloons of the same colour close together. This scale creates enough separate segments for these regions and also clearly segments pieces of balloons that are overlapped by other balloons. Please refer to figures 2.1.2 and 2.1.3 on page 4.

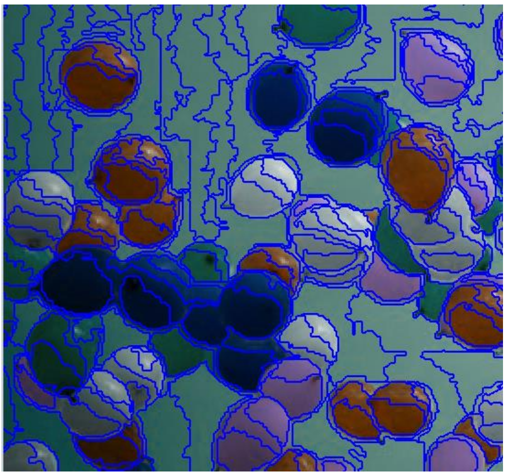
Figure 2.1.2 Balloon Clumps

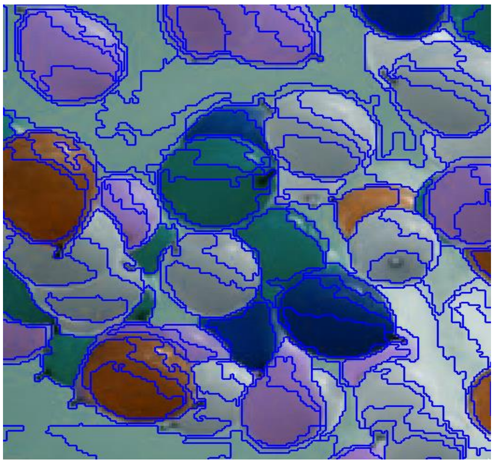
Figure 2.1.3 Overlapping Balloon

2.2 Choosing features

The features are arranged in a hierarchy. A distinction between the background and the balloons is first made. The balloons are then each distinguished from each other and the background differentiates between clear blue sky and cloud cover. The image below in figure 2.2.1 shows the classes.

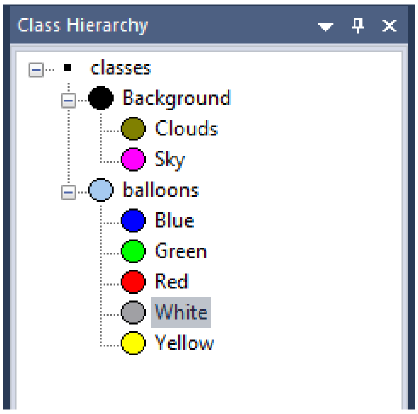

Figure 2.2.1 Classes

The classification is then added to the process tree. eCognition performs the Nearest Neighbour classification on the image. The feature space is populated with the colour (RGB) and the shape (roundness) geometries of the objects.

In figure 2.2.2 and 2.2.3 below the images of the different classification levels are shown. There are regions that are incorrectly classified, but most of the balloons and background are classified accordingly.

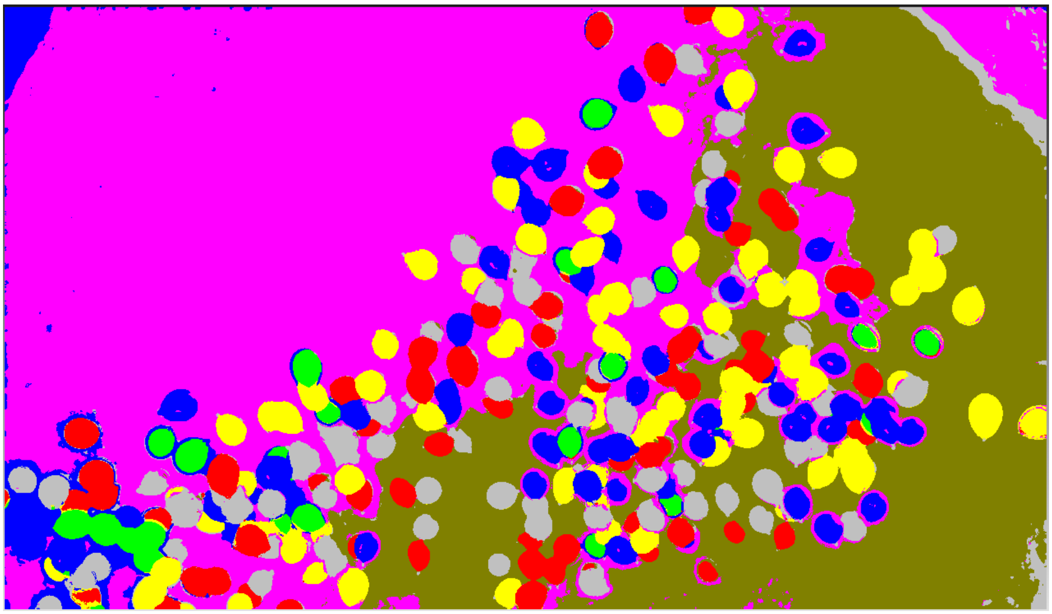

Figure 2.2.2 Classified Balloons and Background

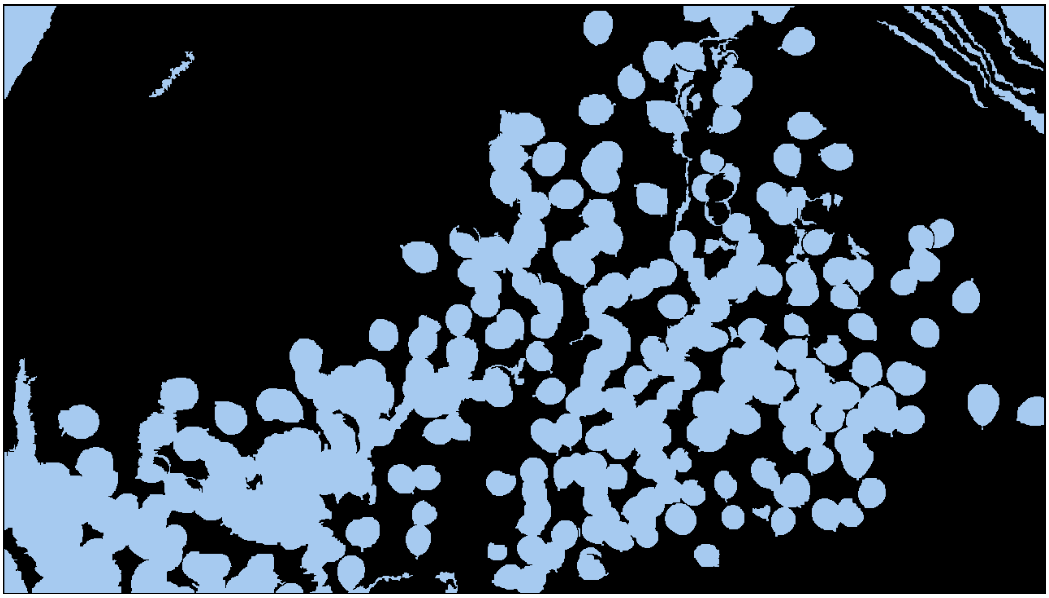

Figure 2.2.3 Classified Image

Choosing to distinguish between the objects based on colour is useful in separating the balloons from each other to be counted accordingly. Classification based on shape is helpful in differentiating between the background, made up of blue sky and clouds and the balloons themselves since they are very rounded in comparison to the other objects in the image.

2.3 Decision boundary and counting

The counting of the objects is done using the attribute tables from ArcMap. In order to perform analysis on the classified image, the ISO Cluster Unsupervised Classification tool is used on the classified image to assign the classes to the image in ArcMap. The image output is the same as the classified image from eCognition.

Since it was unnecessary to have the cloud as a classified object for this specific count, I removed it from the classification and took the reclassified image into ArcMap and then performed the ISO Cluster Unsupervised Classification. Below are the relevant images labelled figure 2.3.1 and figure 2.3.2 respectively.

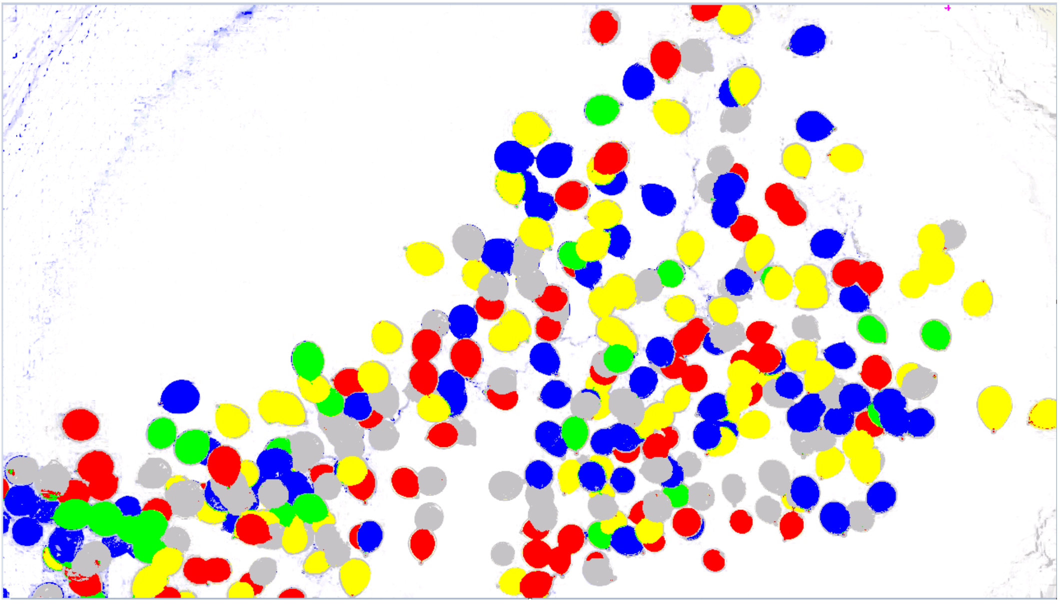

Figure 2.3.1 Classification without Cloud

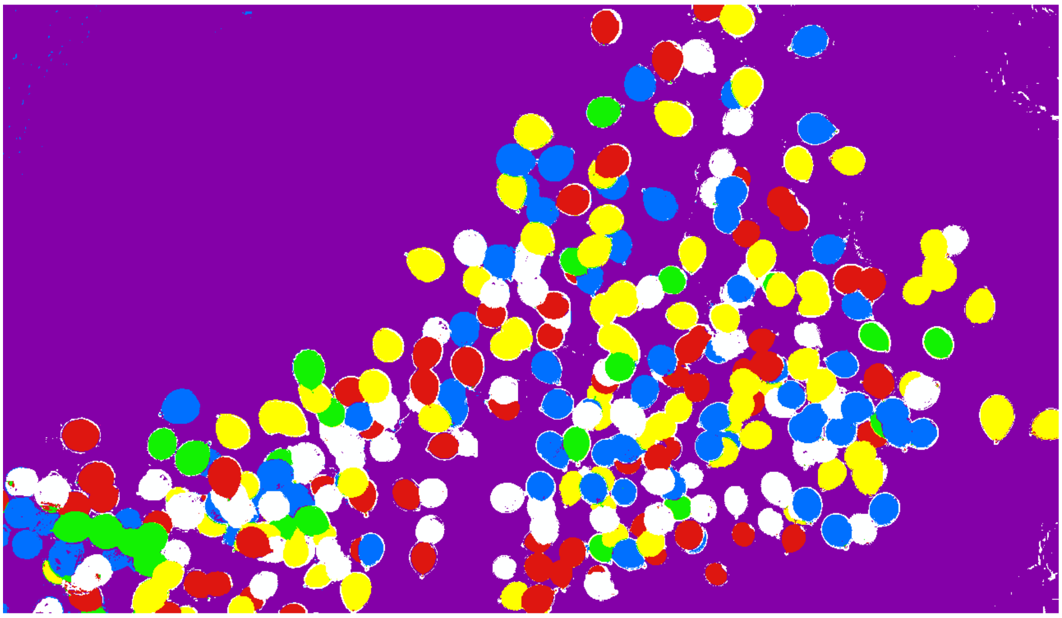

Figure 2.3.2 ISO Cluster Unsupervised Classification

The classified image is a raster. In order to count the objects in the image, the raster is converted using the Raster to Polygon tool in ArcMap. In the attribute table of the polygons we can see the shape areas and the grid codes. Using these attributes we can sort and clean the polygon layer to keep the necessary information and remove noise.

Since the count is of the balloons in the image, the entire background is essentially noise in the image. Another presentation of noise are polygons of very small areas that are less than 90. The background is removed by deleting attributes with the grid code for background. Areas below 90 are also removed using the attribute table.

There are balloons that are the same colour and overlapping and therefore their areas are merged to form one very big polygon. To sort these, the single balloons are removed using their areas. Multiple balloon polygon areas are mostly greater than 1350. Using an interval for area < 1350, the single balloon polygons are separated from the multiple balloon polygons. Since these polygons contain more than one balloon, their area is divided to calculate how many balloons possible exist in them. An interval of 300 < area < 1350 is used and the mean shape area is used as to divide the large polygons. Areas less than 300 are pieces of balloons that are overlapped by other balloons of different colours or are cut out of the image frame. Figure 2.3.3 illustrates this attribute selection in ArcMap. The mean area was found to be approximately 885 (rounded).

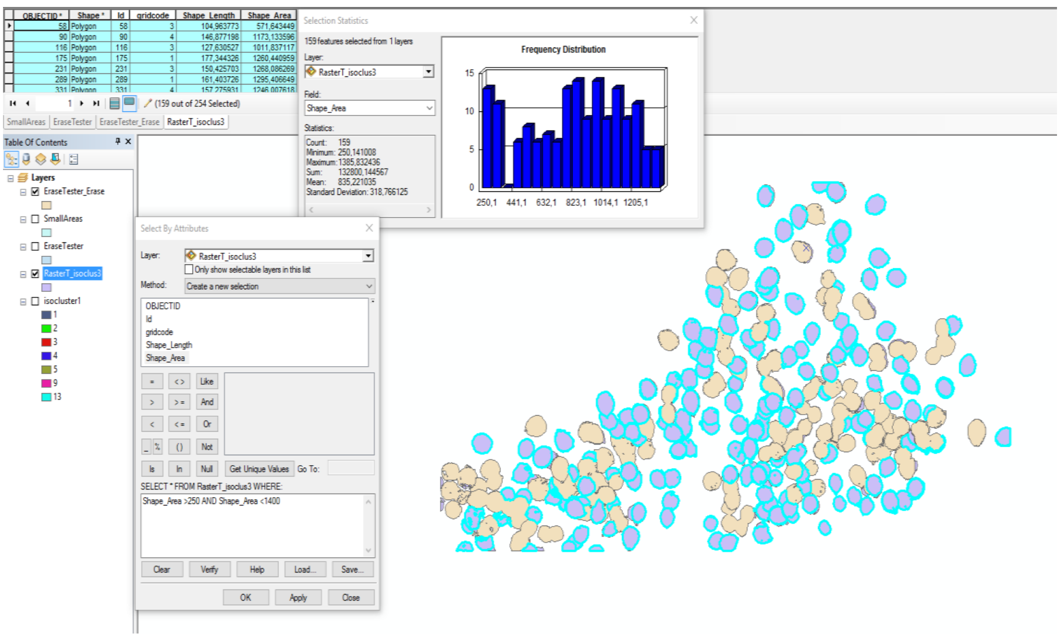

Figure 2.3.3 Attribute Selection

3 Results

As mentioned before, the classified eCognition image was taken into ArcMap where the classification accuracy was tested as well as the attribute table generated for counting. The results are all attained using the data from ArcMap.

3.1 Classification

The test region is created by generating stratified random points on the image using the Create Accuracy Assessment Points tool in ArcMap. Each point has a classified and a ground truth attribute. The point feature class contained 101 points and each of the ground truth attributes had to be corrected to what they were on the original image. These points are then used as the input data for the confusion matrix generation tool. The final output is a table (matrix). Figure 3.1.1 below shows the confusion matrix representing the quality of the classification.

ClassValue	BlueBalloo	GreenBalloo	RedBalloo	YellowBallo	WhiteBalloon	Background	Total	U_Accuracy	Kappa
BlueBalloons	10	0	0	0	0	0	10	1	0
GreenBalloons	0	9	0	1	0	0	10	0.9	0
RedBalloons	0	0	10	0	0	0	10	1	0
YellowBalloons	0	0	0	9	0	1	10	0.9	0
WhiteBalloons	1	0	0	0	7	2	10	0.7	0
Background	0	0	1	0	1	49	51	0.960784314	0
Total	11	9	11	10	8	52	101	0	0
P_Accuracy	0.909090909	1	0.909090909	0.9	0.875	0.942307692	0	0.930693069	0
Kappa	0	0	0	0	0	0	0	0	0.899844171

Figure 3.1.1 Confusion Matrix

The Kappa statistic is a measure of how closely the classified image matched the ground truth of the points. The Kappa value of 0.89984 shows that the classifier performed with an accuracy of almost 90%.

3.2 Object Count

Balloons having areas less than 300 were mostly the sing balloons and were grouped together using the selection by attributes to define their area interval. A new layer was made from these balloons. The remaining balloon layer is then 'clipped' to the new layer to remove repeat polygons from overlapping and possible merged balloons. The remaining balloons with very large areas are then divided by the average area to gain an approximate number of balloons contained in each large polygon area. I decided to round down the balloon count. The attribute tables are exported and counting is done in excel. An example of the attribute table in the Excel spreadsheet is shown in figure 3.2.1 on page 8.

OBJECTID	Id	gridcode	Shape_Length	Shape_Area	balloons	rounded
5	797	1	494.5621252	4422,180819	4.9968143	4
7	835	1	208.3823207	1954,175978	2.2081084	2
22	2413	1	157.4759541	1517,213841	1.714366	1
26	2768	1	162.0048713	1559,438763	1.7620777	1
27	2798	1	233.2569361	1979,511154	2.2367358	2
28	2833	1	276.4958386	2675,940947	3.0236621	3
31	3017	1	318.0494038	2124,361799	2.4004087	2
32	3069	1	226.9347332	1619,137784	1.8295342	1
40	3721	1	428.5982496	2418,901513	2.733222	2
47	4174	1	430.3472821	2811,410511	3.1767349	3
175	175	1	177.3443261	1260,440959	1	1
289	289	1	161.4037258	1295,406649	1	1
333	333	1	114.4305751	450,9867558	1	1
466	466	1	149.2978311	1237,55446	1	1
681	681	1	123.5588966	575,9685311	1	1

Figure 3.2.1 Blue Balloon Attribute Table Export

The table in figure 3.2.1 shows the total balloon count for each of the different colours of balloons. The count includes pieces of balloons that are behind each other and overlapping balloons.

<u>Table showing the count of balloons</u>

Total number of balloons in the image	267
Total blue balloons	59
Total green balloons	21
Total red balloons	57
Total yellow balloons	66
Total white balloons	64

Figure 3.2.1 Table with count data

4 Conclusion

Based solely on the kappa and the confusion matrix results, the classifier proves to be well fitted to the data. However, the information provided by these statistics can be better consolidated by performing testing on other possible classifiers and then comparing the kappas or by using other features to populate the feature space. These features vary extensively. For this assignment only two features were selected as mentioned in the methodology section of this report. This is to ensure the feature space dimension is kept minimal to reduce the complexity of the classifier.
The kappa value can also be made more reliable by retesting using a new set of assessment points, but since the classifier has proven to be good enough, I chose not to do so.

The count of the balloons also seems to be realistic to what the image displays.

There is always room for improvement when it comes to perfecting the solution, but as far as my own knowledge and ability to put my understanding into practice goes, the results are conclusive to a good classification of the image and the count works and is realistic.