GCP Segmentation in Aerial images

Objective: Segment the ground control points for aerial images

Observations about the problem statement:

- The size of the GCPs are very small
- Color distribution is almost same across the whole dataset
- There are no distinctive texture features but the shape of the GCP is same.

Approach:

In order to segment such a small object, segmentation has to be done on pixel-level. I came up with two approaches for this segmentation.

1. Gaussian Mixture Color Modelling from a sample of GCP's:

- In this approach, I first created a GUI script for segmenting only the GCP from some of the images (around 6 samples) and then logged the RGB and HSV values in the selected region. I stored it in .npy file and then modelled that data into a Gaussian Mixture model with two components.
- Now, once the modelled is trained on this data, prediction is done on a query image. The RGB/HSV data of the query image is reshaped into Nx3 vector. Each row is a query sample and prior probabilities are calculated for each sample.
- Top 10% percentile of probabilities are selected and the corresponding samples are marked as foreground. The output mask segments the GCP accurately, but along with some other components with same color distribution in the image.
- In some of the cases, where GCP is very small, the model segmented only very less part of the GCP.
- Therefore, the output of the Gaussian model is used as markers for watershed algorithm which reconstructs the GCP properly.

2. Superpixel to divide the image into contours and then test individual contour for properties like color, shape of the contour:

- In this approach I tried SLIC (Simple Linear Iterative Clustering) and Felsenszwalb's graph based segmentation. The results of the later were very good. A tight contour was always formed around the GCP.

- But as the runtime was really high, due to large size of the image and lack of computation power available I could not move further with this approach.

Here are the samples of segmentation done using GMM modelling followed by watershed.

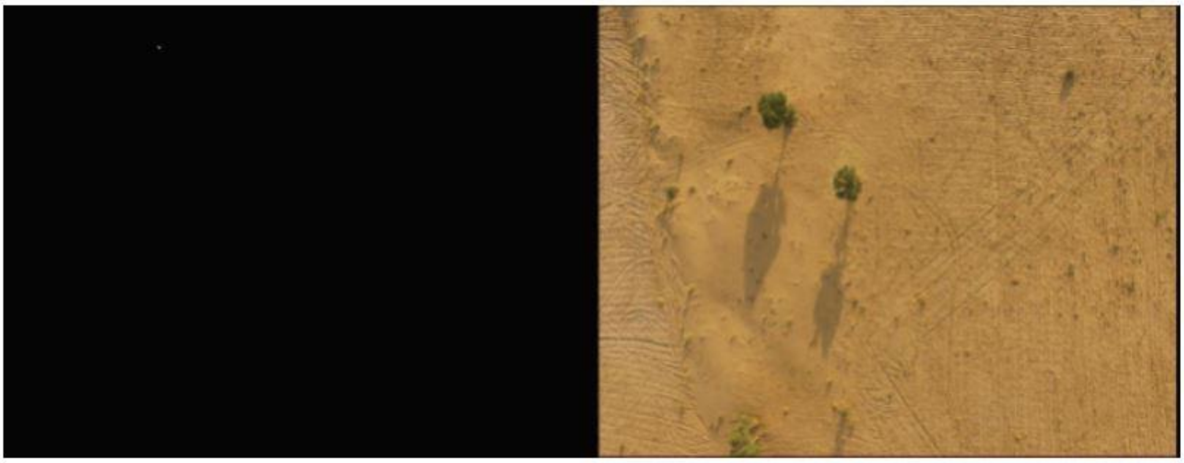


Fig 1.

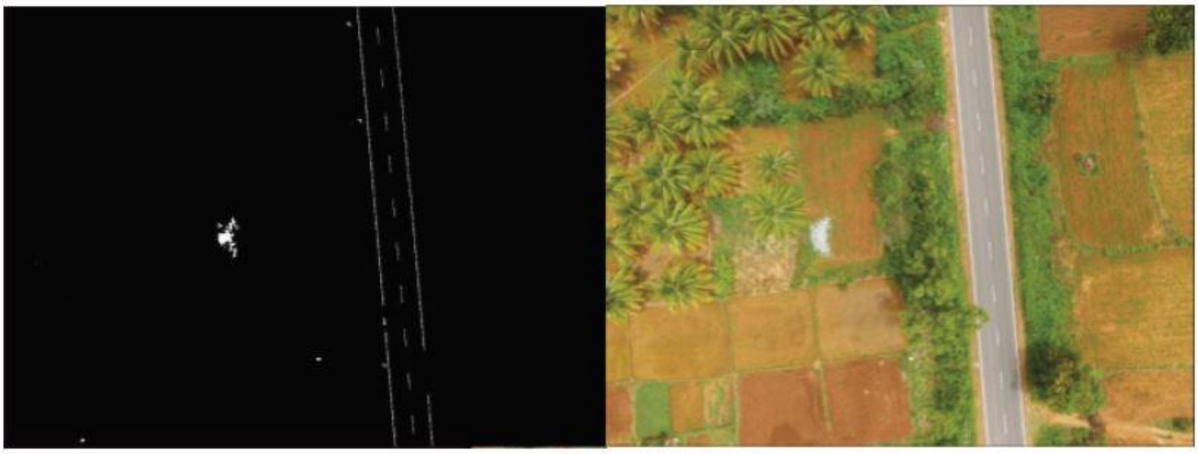


Fig 2.

After segmentation there are other contours also that are segmented. We need to rule out those contours which are not similar to the shape of L and have almost equal arm lengths.

I tried various approaches in order to model the shape of 'L'. Hu Moments and Zernike moments are considered as good shape descriptors which are invariant to translation as well as rotation. Therefore, at first I tried and extracted Hu moments from the 6 sample GCPs initially used for color model. But I realized that 6 samples were not enough therefore I increased the number of samples by rotating and flipping those samples. I tried different models in order to model Hu features like Gaussian mixture and a random forest classifier. In random forest classifier for negative class I took random contours and some of the segmented contours in the sample images. Individually the results of random forest classifier were not up to the mark.

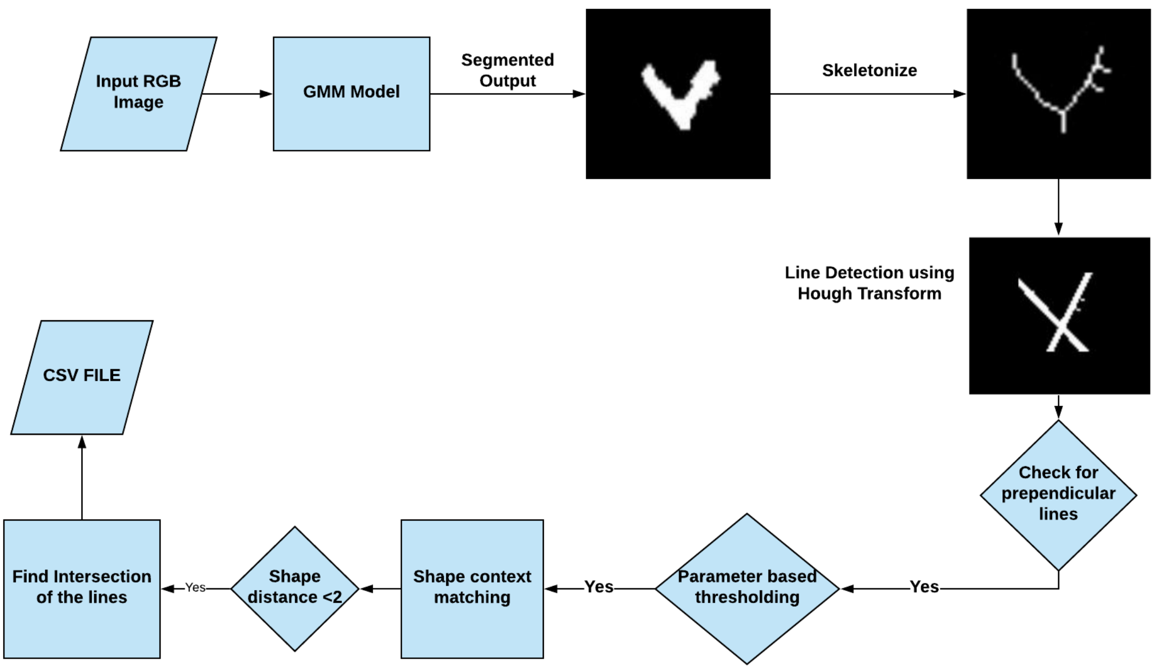
Therefore, in order to segment on L shaped contours I tried the approach of detecting lines in the cropped segments. In this approach the two most prominent lines are detected which have minimum angle of 80 degree between them. The lines are detected on the skeleton of the contour in order to avoid near duplicate lines. Then many parameters like compactness, number of vertices, ratio of the lengths of the arms of GCP etc. are calculated. The values of these parameters must lie in particular range for a GCP.

Instead of Random Forest classifier now I am using shape context for shape matching. Some sample shapes are placed in the crop folder Shape context was introduced in the following paper:

Shape Context: A new descriptor for shape matching and object recognition, Serge Belongie, Jitendra Malik and Jan Puzicha, 2001, NIPS proceeding.

Shape context matches shape by fitting the shape into a set of angular and radial bins. It also calculates the bending energy and weights is given to that also in the final distance calculation. The sample which pass the test of intersecting perpendicular lines are test for shape context.

Process flow can be visualized in below flow diagram:



Other approaches that were tried:

- Generalized hough transform is a method to detected generalized shapes in an image. We need to set the parameters of the shape to be detected. It works in the same way hough line transform or hough circle transform. It is very particular to the shape and thus is not very robust when the segmentation is not proper in the image.
- Training a classifier on the cropped images of the GCP by extracting SIFT/SURF/ORB features from the training images. RGB features could also be concatenated with these using Bag of visual words method. At the time of inference first the segmentation has to be done using GMM. The bounding boxes of contours that are detected can be used to crop the RGB image and then label could be predicted. This approach must be theoretically more robust, but would require more data so that it can be trained efficiently.

Conclusion:

The segmentation modules is able to segment GCP in almost every image. The shape context model improves the shape classification. GMM with shape context produced the best results out of other approaches that were tried.