Classification Software Package – Algorithm Outline

**Learning a geometric star model representation for an object class**

1. Select a training image set with positive (class) exemplars and negative (non-class) exemplars.
2. Extract image fragments of various sizes with some overlapping (⅓ of the fragment size) from the class training images.
3. Select a set of N (N=150) informative fragments using the Max-Min algorithm.
4. Measure the similarity (SIFT or NCC) of all informative fragments at each pixel position in all class training images, and find the location of the maximum similarity measure of each fragment in all training class images.
5. For each training class image, set the initial object center at the mean location of the detected fragments (each at its maximum similarity location).
6. Calculate the relative offsets between fragments' locations and object center locations in each of the training class images.
7. Using the first training class image fragments' offsets from the initial object center location, create a voting map to a refined object star center location for each of the remaining training class images. The voting map is constructed by adding a 10x10 uniform rectangular window at the voted object center location positioned at the relative offset from each of the fragments detection location. Each 10x10 rectangular window is of weight equal to the corresponding fragment's Max-Min weight. The refined (voted) object star center location is at the mean location of the voting map's highest value area.
8. Recalculate the relative offsets between fragments' location and the refined (voted) object center locations in each of the training class images.
9. For each of the fragments count the number of training class images in which the fragment is an outlier, i.e. its offset from the refined (voted) object star center is bigger than a predefined threshold.
10. Repeat steps 7 through 9 while using the initial offsets of each of the training class images to find a refined (voted) object star center location in the remaining training class images.
11. Select the image whose initial offsets yield the lowest maximum number of training class images containing outlier fragments (among all fragments), and the minimum total number of outlier fragments among all training class images.
12. Discard of the outlier fragments, based on the selected training class image initial offsets and refined (voted) object star center location.
13. For each of the remaining fragments (non-outliers), calculate the mean and covariance of fragments' offsets from the voted object star center locations in each of the training class images.
14. Discard fragments with high offset variance or with too few training images in which the fragments were detected in (relative a calculated detection threshold).
15. Use the mean fragments' offset and covariance as a star model to represent the geometry of object parts, in which the pair-wise dependency between each object part and the object star center is modeled with a Gaussian with mean and covariance of the corresponding fragment's offset.

**A simple geometric voting star model classifier**

16. Recalculate object star center locations in each of the training class images, utilizing a voting map mechanism similar to the above, with the exception that instead of using uniform 10x10 windows to vote for the object star center, a rectangular Gaussian window is used with dimensions twice as the Gaussian's variance (also weighted with the Max-Min fragment's weight).

17. Measure fragments' similarities in each of the training non-class images and find the maximum similarity locations. Use the detected fragments' locations (with maximum similarity which is higher than the detection threshold) to vote for a star center location with the above pair-wise Gaussians model.

18. Utilize ROC approach to calculate a classification threshold on the star center voting scores (use the voting results of the training class and non-class exemplars found in steps 16 and 17). Both equal error rate (EER) threshold and minimum total error rate (MTER) threshold are calculated.

**A semantic geometric voting star model classifier**

19. Use the star model offsets from step 15 and the voted object star center locations from step 16, to extract fragments from all training class images. All fragments extracted with the same offset from the star center are stacked together and used as candidates for creating a part detector scheme, with multiple semantic equivalent fragments, that represent multiple appearances of the object part.

20. Train the CNOR semantic object part detector on all training class images.

21. Update the geometric star model by replacing each fragment with its corresponding semantic part detector and refined offset from the object star center (use the same covariance matrix from step 13).

22. Find the locations of maximum similarity of each of the object part detectors in all training images (both class and non-class), and vote for the object star center locations.

23. Follow step 18 to find classification thresholds on the star center voting scores, using an ROC approach.