OUTLIER COLOR DETECTION IN SEARCH AND RESCUE

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1. Introduction

The background of this project is to find human victims from wild scenes in the searching and rescue scenario. This project focus on finding the object of interest, probably human victims with distinct color from surrounding in a wild scene image. The image is taken in large scale, high resolution and aerial view. A natural landscape would likely exhibit some similar patterns and colors.

2. Solution

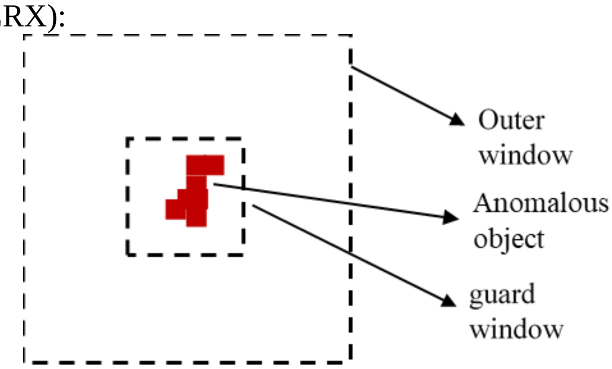
2.1 RX-Algorithm

RX algorithm assumes the image follows multi-variate Gaussian distribution and each pixel is a realization drawn from the distribution. In general, the RX algorithm employs Mahalanobis distance as a measure to determine how far two attributes deviate from each other. Mahalanobis distance is given by $D^2 = (\boldsymbol{x} - \boldsymbol{\mu})^T \boldsymbol{C}^{-1} (\boldsymbol{x} - \boldsymbol{\mu})$, $\boldsymbol{\mu}$ is an estimated mean of the distribution; $\boldsymbol{C}$ is the covariance matrix. $\boldsymbol{\mu} = \frac{1}{M} \sum_{i=1}^{M} \boldsymbol{x}(i)$, $\boldsymbol{C}_{ij} = cov(\boldsymbol{x}(i), \boldsymbol{x}(j))$. $\boldsymbol{\mu}$ and $\boldsymbol{C}$ could be estimated either from the whole image or from local pixels.

Global RX-Algorithm (GRX):

- Calculate the mean $\boldsymbol{\mu}$ and covariance matrix $\boldsymbol{C}$ with all pixels in the image
- Calculate $D^2 = (\boldsymbol{x} - \boldsymbol{\mu})^T \boldsymbol{C}^{-1} (\boldsymbol{x} - \boldsymbol{\mu})$ for all pixels in the image
- Those pixels with large D^2 are anomalous pixels

Local RX-Algorithm (LRX):



- Using a sliding dual-window to perform this algorithm on each pixel in the image
- For each pixel, calculate the mean $\boldsymbol{\mu}$ and covariance matrix $\boldsymbol{C}$ with all pixels in the outer window
- Calculate $D^2 = (\boldsymbol{x} - \boldsymbol{\mu})^T \boldsymbol{C}^{-1} (\boldsymbol{x} - \boldsymbol{\mu})$ for all pixels in the image
- Those pixels with large D^2 are anomalous pixels

Cluster Kernel RX-Algorithm (CKRX)

- Packing background pixels into several groups using k-means $\mathrm{C} = \{(\boldsymbol{z_1}, s_1), (\boldsymbol{z_2}, s_2) \ldots (\boldsymbol{z_m}, s_m)\}$, z_i is the representative of the group, s_i is the number of pixels in this group, m is the number of groups.
- Construct kernel matrix: $\boldsymbol{K}_{i,j} = k\left(\boldsymbol{z_i}, \boldsymbol{z_j}\right)$, $k(\boldsymbol{x}, \boldsymbol{y}) = e^{\left(\frac{(-\|x-y\|^2)}{c}\right)}$
- Compute mean vector: $\boldsymbol{\mu} = \boldsymbol{Kw}$, $\boldsymbol{w} = \frac{s_i}{\sum_{i=1}^{m} s_i} \times \text{ones(m, 1)}$
- Subtract mean for kernel matrix: $\widehat{\boldsymbol{K}} = \boldsymbol{K} - \boldsymbol{\mu e}' - \boldsymbol{e\mu}' + \boldsymbol{ew}'\boldsymbol{\mu e}'$, $\mathbf{e} = \text{ones(M, 1)}$
- Perform eigendecomposition for PCA: $\widehat{\boldsymbol{K}}\boldsymbol{S} = \boldsymbol{VDV}'$, S is a diagonal matrix with $S_{ii} = S_i$
- Extract $\overline{\boldsymbol{D}} = \boldsymbol{D}(1{:}t, 1{:}t), \overline{\boldsymbol{V}} = \boldsymbol{V}(:, 1{:}t)$, where $\boldsymbol{D}(\mathrm{t}+1, \mathrm{t}+1) < \boldsymbol{D}(1,1) \times 10^{-8}$
- Compute anomaly value : $\boldsymbol{v} = \|\overline{\boldsymbol{D}}^{-1}\overline{\boldsymbol{V}}^{T}(\overline{\boldsymbol{\gamma}} - \overline{\boldsymbol{\mu}})\|_2$, $\overline{\boldsymbol{\mu}} = \boldsymbol{\mu} - \boldsymbol{ew}'\boldsymbol{\mu}$, $\overline{\boldsymbol{\gamma}} = \boldsymbol{\gamma} - \boldsymbol{ew}'\boldsymbol{\gamma}$, $\boldsymbol{\gamma} = k(\boldsymbol{x}_i\ , \boldsymbol{r})$

2.2 KNN-distance Method

- Find the kth-nearest neighbor for each pixel in the image in Lab color space
- Compute the Euclidean distance of the kth-nearest neighbor (KNN-distance) for each pixel and draw a histogram
- Decide the threshold of anomalous distance by counting the number of pixels falling into each interval from the greatest distance to smallest.
- Use Markov random field (MRF) model to eliminate false positive and make true positive salient
- Construct Gaussian mixture model (GMM) for each positive objects and their surrounding separately.
- Use K-mean with KL-divergence of GMM of background and positive object to further eliminate false positive

3. Experiments

Figure-1, The mountain with anomalous object inserted

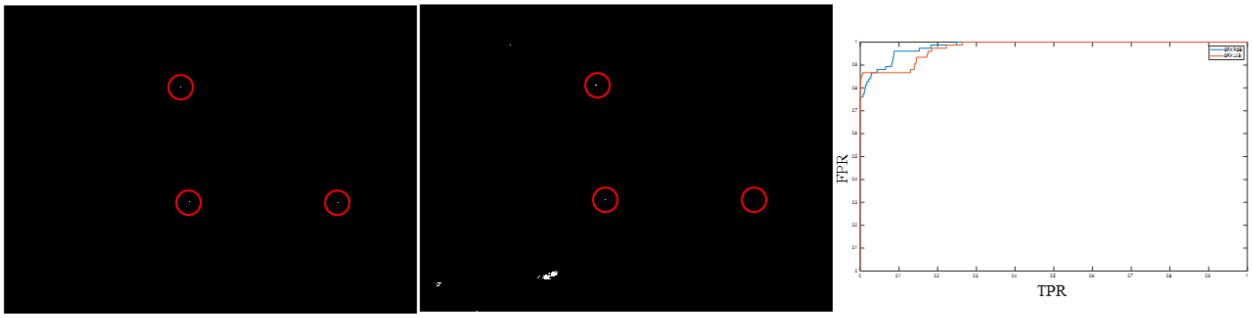


Figure-2, result from GRX-RGB (left), LRX-Lab (middle), and their ROC (right), the TP is marked out by circle

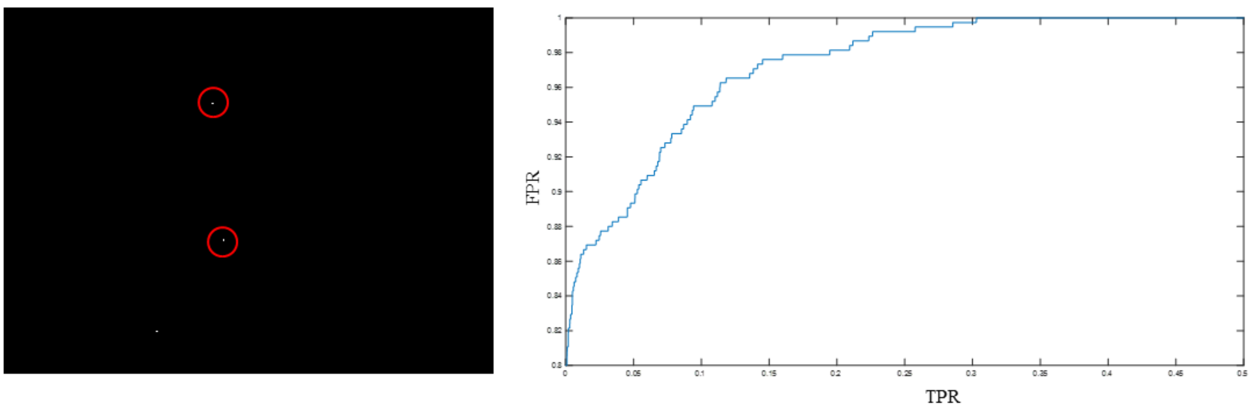


Figure-3, result from CKRX (left), its ROC (right), the TP is marked out by circle

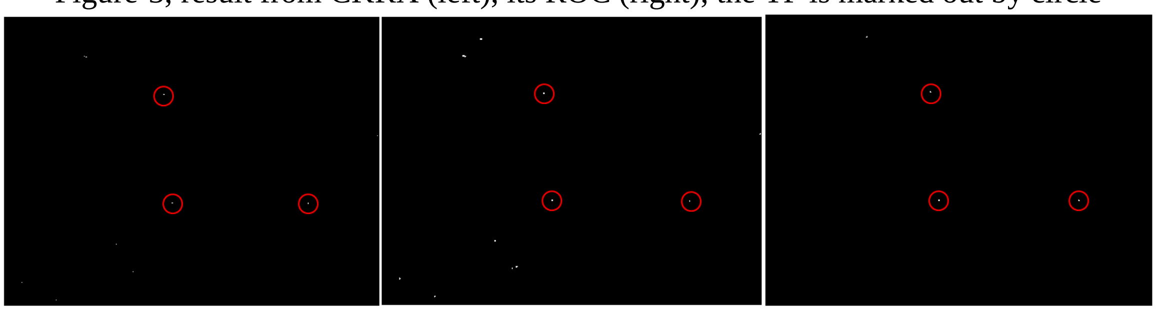


Figure-4, result from KNN-distance, with only thresholding (left), adding MRF (middle), adding k-mean with KL-divergence(right), the TP is marked out by circle

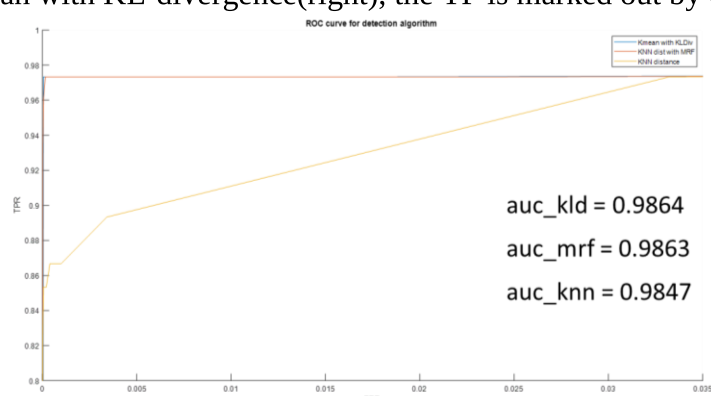


Figure-5, ROC for KNN-distance method with each auxiliary steps

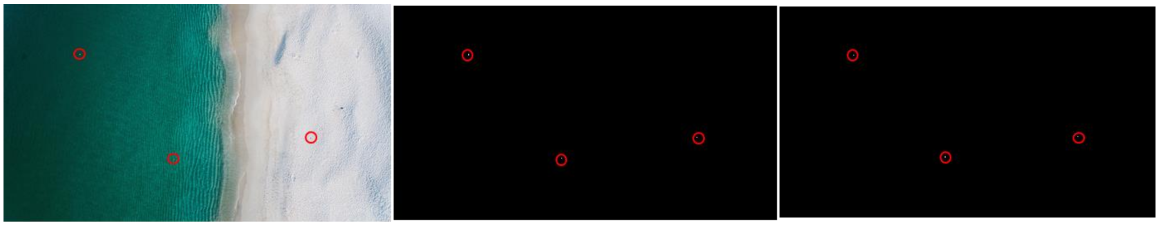


Figure-6, Test on Beach scenario, original (left), GRX (middle), KNN-distance with all auxiliary (right), the TP is marked out by circle

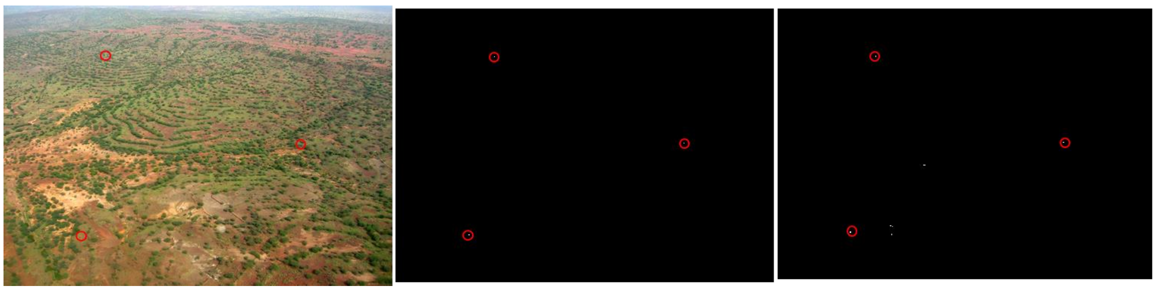


Figure-7, Test on barren land scenario, original (left), GRX (middle), KNN-distance with all auxiliary (right), the TP is marked out by circle

4. Conclusion

From our work, we can learn that GRX is the simplest but effective method. It works well even in a rather complicated environment. Meanwhile, the computational cost is extremely low for GRX rather than other RX algorithm, which is acceptable. The computational cost for other RX algorithms is extremely high, especially for KRX, CKRX, and LRX. Additionally, CKRX algorithm also faces many risks in computation, such as singular matrix, k-means not converge. These risks can also harm performance.

KNN-distance is another applicable approach, and the auxiliary process adding to the methods is effective to improve efficiency by eliminating the false positive. The computational cost for KNN-distance is lower than the GRX. However, such an approach is sensitive to parameters (especially in the GMM step) which should be well tuned for each case.

For the future step, we can try to deal with this problem in a sequence of images, which is more close to a real scenario and could possibly exploit some feature along the time to solve this problem. We can also explore a method to adjust the threshold automatically for GRX. For KNN-distance search, the professor has pointed out that MRF is not a good method in this approach, dilation and erosion can server as a better solution.