Group A0: Pixel-wise anomaly detection for AOS

Computer Vision Project 2021/2022

Pablo Díez Arrizabalaga Christian Willdoner René H. Reich

Laura Legat Daniel Schatzl

ABSTRACT

In this document, the project for the computer vision laboratory 2021/22 of group A0 is described. Avoiding deep learning models, we developed an unsupervised model based on classical computer vision techniques capable of detecting moving anomalies in multiperspective images.

KEYWORDS

pixel-wise, anomaly detection, mask, occlusion, merging, unsupervised, forest, wood, human, rescue

1 DESCRIPTION

Initially, the procedure presented in [1] was considered. Nevertheless, the unsatisfactory results obtained made us neglect both the Autoencoder and the Discriminator from our model, and only contemplate the RX detector. Along the same lines, using the OpenCV library we were able to apply classical image masking methods. Thus, our final pipeline is shown in Fig. 1 and Fig. 2.

The database was composed of several samples each containing 7x10 images, 7 timesteps for 10 different views of the same scene. By merging the images on the camera axis, we obtained 7 images each representing one timestep, of which we only used the 1st, 4th and 7th (last) timesteps. Since we considered that these frames offered enough information to discern the movement of the people to detect from the background.

For the classification of the merged images, a modified Mahalanobis Detector (RX) has been developed, which makes use of the Mahalanobis distance to identify clusters. Once the different clusters are identified, their contours are observed, and a binary image is generated. Afterwards, the binary images corresponding to the 1st and 7th timestep are multiplied, to later check which contours overlap with the 4th timestep, whereas the overlapping contours are considered static and thus removed from the binary image of timestep 4. Around every anomaly in the static-anomaly-free image, an area of interest is defined. If the distribution of RGB values inside this area of interest is outside the distribution of RGB values of all images in the dataset, the anomaly is considered an actual anomaly and is thus kept. Otherwise, it is removed from the binary image. Finally, the bounding boxes are drawn around those anomalies.

Based on this procedure, the average precision on the validation set is 43.33%.

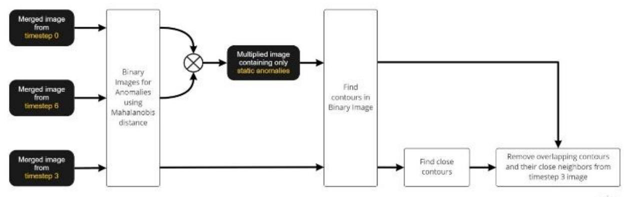

Fig. 1: Remove static objects

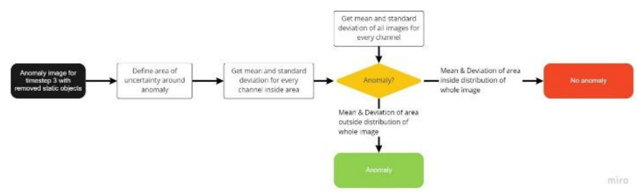

Fig. 2: Anomaly detection

2 ADDITIONAL EXPERIMENTS AND LIMITATIONS

A moving person might appear static when only considering the first and last timestep since there is a possibility that the person moves but ends up (almost) in the initial position. Thus, we tried improving the results by taking into consideration all timesteps. We multiplied the binary images of all timesteps so we could identify the static anomalies and remove them from the binary images of every timestep using the same approach as in the first version. Due to occlusion, people might not be visible in the center timestep, so we added up all static-anomaly-free binary images to include the information of all timesteps. This approach could detect people well, however, it misclassified parts of the background as anomalies. These latter anomalies could not be removed using probabilistic methods.

The method highly depends on hyperparameters. Finding a set of parameters that works well for every image was not possible as changes that led to improvements for some images made the prediction worse for others.

REFERENCES

[1] Sertac Arisoy, Nasser M. Nasrabadi, 2021. Unsupervised Pixel-wise Hyperspectral Anomaly Detection via Autoencoding Adversarial Networks. *arXiv*, 1 (Jan, 2021)