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# Hyperspectral Image Recognition Using Computer Vision

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#### ABSTRACT:

The detection and classification of components in the observed images is made possible by the high spectral resolution of hyperspectral images. However, due in part to the limited spatial resolution in common earth observation applications, current research on hyperspectral detection primarily concentrates on pixel-level studies. High-spatial-resolution hyperspectral data can now be collected because to advancements in imaging techniques, and object-level detection is now required for many applications. This study formulates the object-based hyperspectral identification problem and designs a convolutional neural network based on the unique properties of this challenge. The first semi-supervised hyperspectral object detection (SSHOD) challenge was held as a part of the Perception Beyond the Visible Spectrum (PBVS) 2022 workshop at the Computer Vision and Pattern Recognition (CVPR) conference. This article lists the best submissions to the challenge. The SSHODC challenge is a pioneering hyperspectral dataset with temporally contiguous frames that was gathered over three days from a university rooftop while observing a 4-way automobile intersection. The collection consists of 2890 frames altogether, with 51 hyperspectral bands from 400 to 900 nm, with an average resolution of 1600 192 pixels. The training set for the SSHOD challenge consists of 989 photos, the validation set of 605 images, and the evaluation (test) set of 1296 images. To maximise, each set was purchased on a different day.

Keywords: Hyperspectral imaging, target detection, Object based detection, convolutional neural network, Pattern Recognition.

## **INTRODUCTION**

Modern computer vision algorithms allow for the use of a wide range of computer vision applications, from security to the medical industry. The primary characteristic of computer vision is to mimic some of the complexity of the human visual system and make it possible for computers to recognise and analyse things in pictures and videos in a manner similar to that of humans. Common vision systems frequently fail to distinguish between objects with similar colours or looks. In these circumstances, spatial pattern recognition algorithms and hyperspectral data can identify a variety of materials, patterns, coatings, flaws, and pollutants. Automated picking and sorting of materials is made possible by hyperspectral vision systems, which produce data for quality control and also convey information to robotic actuators.

In contrast to traditional colour (RGB) photographs, which contain three bands of colour, hyperspectral imaging (HSI) has around 50–400 contiguous colour bands. The enhanced detail of the object materials presents in the scene that results from this increase in resolution along the channel dimension has been shown to improve fine-grained discrimination in deep neural networks for hyperspectral pixel classification, object tracking, and super-resolution [8-10, 13, 14, 21, 27].

#### LITERATURE SURVEY

[1] Ohad Ben-Shahar and Boaz Arad. The phrase "Sparse recovery of hyperspectral signal from natural rgb images" is used.

- The author discusses the sparse recovery of hyperspectral signal from natural RGB photos in their publication. In the areas of compressed sensing, signal de-noising, statistical model selection, and others, sparse recovery is referred to as a difficulty.
- As the hyperspectral setup is even more complex and expensive, it mostly covers how the hyperspectral images are recovered from the RGB.
- Here, simply RGB is utilised as an input, and the goal is to produce hyperspectral images that are both quickly and inexpensively obtained at high spatial and spectral resolution.
- This article seeks to convert RGB picture data from a 2D imaging sensor into a 3D data cube of a hyperspectral image.

[2]. Vasconcelos and Nuno Zhaowei. "Investigating high quality object detection" with Cascade R-CNN. 2018 IEEE Conference on Computer Vision and Pattern Recognition Proceedings, pp 6154–6162

- The author discusses the sparse recovery of hyperspectral signal from natural rgb photos in their publication. In the areas of compressed sensing, signal de-noising, statistical model selection, and others, sparse recovery is referred to as a difficulty.
- As the hyperspectral setup is even more complex and expensive, it mostly covers how the hyperspectral images are recovered from the RGB.

- In this case, the sole input used is RGB, and the output is the ability to swiftly and affordably acquire hyperspectral images with excellent spatial and spectral resolution.
- This article seeks to convert RGB picture data from a 2D imaging sensor into a 3D data cube of a hyperspectral image.

[3]. Wei Wei, Yanning Zhang, Shengcai Liao, Lei Zhang, Jiangtao Nie, and Ling Shao. "Unsupervised adaptation learning for super-resolution hyperspectral imaging." Pages 3073-3082 of the 2020 Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition.

- The author of this paper discussed the Hyper Transformer, a textural-spectral feature fusion network for HS pansharpening that uses a multihead feature attention mechanism to convert HR textural characteristics from PAN images to spectral features from LR-HSI.
- Hyperspectral (HS) pansharpening aims to spatially enhance low-resolution hyperspectral pictures (LR-HSIs) by transferring textural (spatial) information from panchromatic (PAN) images with higher spatial resolution while keeping the spectral features of LR-HSIs.
- Major advances in HS pansharpening greatly increase the spectral and textural information in HSIs, which is an essential pre-processing step for many remote sensing applications to precisely and quickly identify the underlying phenomena that would otherwise be difficult to see from image to LR-HSI.
- Deep convolutional neural networks (Conv Nets), which excel in picking out the right photo features, have now been presented for HS
  pansharpening.

[4]. Reconstruct hyperspectral images from a snapshot measurement by Xin Miao, Xin Yuan, Yunchen Pu, and Vassilis Athitsos. Pages 4059–4069 in the 2019 Proceedings of the IEEE/CVF International Conference on Computer Vision

- The author of the research describes how hyperspectral images were reconstructed from a single shot measurement. Typically, this activity is known as snapshot compressive-spectral imaging (SCI).
- Snapshot compressive-spectral imaging (SCI) is a term used to describe compressive imaging systems that map many hyperspectral frames into a single measurement and have low costs. Multiple hyperspectral frames are mapped into a single measurement in compressive imaging systems known as snapshot compressive-spectral imaging (SCI). The coded aperture snapshot spectrum imaging system was the first SCI system (CASSI)
- In this way, a two-dimensional (2D) monochromatic digital camera can capture hyperspectral scenes at video rate, saving memory, bandwidth, and money relative to using a traditional spectrometer in addition to high-speed sensing.
- Reconstructing the 3D hyperspectral data-cube from each snapshot measurement following the sensing process is one of the key steps in SCI.

[5] Adaptive fusion of hyperspectral probability maps for aerial vehicle tracking by Burak Uzkent, Aneesh Rangnekar, and Matthew J. Hoffman. Page number: 233-242 in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops. IEEE, 2017.

- This study focuses on aerial object tracking, which has a wide range of uses in security, traffic surveillance, self-driving cars, and UAV
  monitoring. A variety of data modalities, including but not limited to grayscale, thermal, colour, and more recently, hyperspectral photography,
  can be used for tracking from airborne platforms. Additionally, we'll concentrate on two distinct sensor modalities: adaptive hyperspectral
  images and wide-area motion imaging (WAMI).
- With the use of this extra spectrum data, pre-trained deep architecture in a tracking framework can be used more successfully. Furthermore, the use of spectral data can reduce the need for data collection with higher spatial resolution.
- Here, using a synthetic hyperspectral video produced by the Digital Imaging and Remote Sensing (DIRSIG) programme, we assess the suggested tracker. We create a sizable single-channel aerial dataset using DIRSIG and train a CNN on it to categorise photos from the actual dataset in order to demonstrate the high-fidelity of this video (WAMI).

## METHODOLOGY

Encryption and decryption using RSA

The author used basic method of sparse recovery of hyperspectral signal from natural rgb images. It presents a low cost and fast method to
recover high quality hyperspectral images directly from RGB.

Early HISs used "whisk broom" scanning, where mirrors and fibre optics are used to capture data, to provide images with great spatial/spectral resolution, such as NASA's AVIRIS. Incoming electromagnetic signals are sent, pixel by pixel, into a bank of spectrometers. In order to acquire images, more recent systems use "push broom" scanning and dispersive optical components and light-sensitive (e.g., CCD) sensors list by list.

Computed tomography imaging spectrometers (CTIS) utilize a special diffraction grating to 'project' the 3D hyperspectral data cube onto different areas of the 2D imaging sensor.

## **RESULT AND DISCUSSION**

### Sparse recovery of hyperspectral signal from natural rgb images

Both RGB samples and their accompanying reconstructed spectra are virtually always well represented by 3 dictionary atoms, as is clear from the methodology and findings we have just described. When it comes to the RGB samples themselves, this could appear anticipated. Our method produces outcomes that are comparable to those of hybrid HS-RGB systems despite using substantially less data for each image than hybrid HS-RGB systems, according to an experimental evaluation that is unprecedented in its scale.

## CONCLUSION

- The paper's basic idea is to employ computer vision from multiple techniques and algorithms to recognise hyperspectral images.
- The Rooftop HSI dataset, a first-of-its-kind dataset to benchmark hyperspectral object detection in realistic circumstances, including occlusion, deformations, and changes owing to weather conditions, is introduced in this study. By labelling only 10% of the training data and encouraging players to apply semi-supervised learning methods to improve performance, we created the SSHOD challenge as a semi-supervised learning scenario.

Hyperspectral imaging uses electromagnetic radiation with wavelengths both inside and beyond the visible spectrum to analyse materials and objects. Finally, we may draw the conclusion that hyperspectral imaging can be utilised to detect infections, hazardous waste, oil spills, and more.

#### REFERENCES

- Boaz Arad and Ohad Ben-Shahar. "Sparse recovery of hyperspectral signal from natural rgb images". In European Conference on Computer Vision, pages 19–34. Springer, 2016.
- Zhaowei Cai and Nuno Vasconcelos. Cascade r- cnn: "Delving into high quality object detection". In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 6154–6162, 2018.
- Lei Zhang, Jiangtao Nie, Wei Wei, Yanning Zhang, Shengcai Liao, and Ling Shao. "Unsupervised adaptation learning for hyperspectral imagery super-resolution". In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 3073–3082, 2020.
- Fengchao Xiong, Jun Zhou, Jocelyn Chanussot, and Yuntao Qian. "Dynamic material-aware object tracking in hyperspectral videos". In 2019 10th Workshop on Hyperspectral Imaging and Signal Processing: Evolution in Remote Sensing (WHISPERS), pages 1–6. IEEE, 2019.
- Burak Uzkent, Aneesh Rangnekar, and Matthew J Hoffman. "Aerial vehicle tracking by adaptive fusion of hyperspectral likelihood maps". In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), pages 233–242. IEEE, 2017.