3 PROBLEM DESCRIPTION

We consider the problem of optimizing the transmission of remotely-captured hyperspectral imaging data over a dynamic channel to maximize the utility of the received data for complex processing tasks such as material identification and classification. This is an important problem for applications such as teleoperation, remote sensing, surveillance, and controlling unmanned systems. As an example scenario, consider a UAV (Unmanned Aerial Vehicle) equipped with a hyperspectral camera dispatched to explore a remote scene. The camera captures a scene across many frequency bands in the spectrum, and needs to transmit the data to a base station for processing and taking actions such as alerting a human operator about the existence of some objects or steering the UAV to a different location. Our problem is to identify the most important components of the hyperspectral data to transmit from the UAV within a *given bit budget* such that the accuracy of the data processing task at the base station is maximized. This problem is more complex, and more general, than the band selection problem addressed in previous works, e.g., [16, 18, 19], where there is no limitation on the amount of data and thus all bands are available at the base station.

The captured hyperspectral data is divided into *cubes*. The dimensions of each cube are x, y, λ, where x, y are the spatial dimensions, and λ is the spectral dimension. Cubes are transmitted successively by the camera to the processing station. Once it receives a hyperspectral data cube, the processing station uses this data as input to a pre-trained *deep learning* model to identify materials and objects in the remote scene using their hyperspectral signatures. The data volume in each cube is, however, very large to be transmitted in a timely manner, even after significant compression. To address this problem, we first propose to encode each band in the hyperspectral data cube into multiple qualities, using any scalable coding method that produces *cumulative* quality layers, i.e., the quality progressively increases by adding layers. For concrete discussion, we use a multi-level two-dimensional discrete wavelet transform (2D-DWT) in our solution. Figure 2 illustrates the considered problem for one cube of hyperspectral data. There are N spectral bands in each cube. Each band can be considered as an image of dimensions x, y. Each band is encoded at Q cumulative quality levels. Then, our problem is to optimally and *jointly* select which bands to transmit and the quality of each band given a bit budget C. It is straightforward to show that this band-quality selection problem is NP-Complete, by reducing the multiple-choice knapsack problem to it. The search space for finding the optimal solution is $O(Q^N)$ in the worst case, which is prohibitive as N is in the order of hundreds of bands for current cameras and Q is usually in the range of 2 to 5 quality levels.

It is important to note that the utility of the received bands is typically a non-linear function. This is because, as illustrated in the left part of Figure 1, spectral bands react differently to various materials in the captured scene, creating the so-called spectral signatures for different materials across the spectrum, which indicates that there is correlation among bands. Thus, depending on the processing task to be done on the received bands, the relative importance of individual band varies. In addition, the possibility of using different qualities for each band adds another level of complexity to the problem, compared to prior works [10, 15, 20].

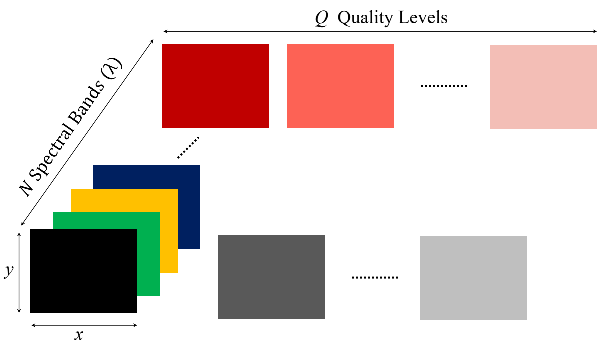

Figure 2: Illustration of the band and quality selection problem for hyperspectral images.

4 PROPOSED SOLUTION

The proposed solution is referred to as BQSA (Band-Quality Selection Algorithm). At high level, BQSA is executed once for each hyperspectral data cube to select bands and their qualities such that a given bit budget for that cube is not exceeded. As discussed in the previous section, jointly selecting bands and their qualities is an NP-Complete problem. We utilize some characteristics of the hyperspectral images to transform this problem into another equivalent problem, which has a substantially smaller search space and thus can be solved in polynomial time (Section 4.1). Then, we design an efficient method to search for the optimal solution in the reduced (polynomial) search space (Section 4.2). Finally, we discuss various optimizations and practical issues (Section 4.3).

4.1 Reducing the Search Space

As discussed in Section 3, the search space is $O(Q^N)$, where Q is the number of quality levels and N is the number of bands, which is prohibitive. To address this, we prioritize the bands and then choose quality levels in a way that substantially reduces this search space. An important feature of our solution is that it retains the physical meaning of each band, that is, it does not mix or transform bands into a different domain where the distinction between bands is lost, as is the case with prior band prioritization methods, e.g., in [10, 14]. This is crucial for utilizing the prioritized bands in achieving classification with different granularities as well as to support various bit budgets.

To prioritize hyperspectral bands, we first transform the 3-D data cube $\boldsymbol{D}_{X\times Y\times N}$ into a 2-D matrix $\boldsymbol{M}_{S\times N}$, where S is the number of pixels in the dataset ($S = X \times Y$). Then, we use PCA (Principal Component Analysis) to extract N principal components from the matrix $\boldsymbol{M}$. Each principal component is a linear combination of bands, which also means that each band has a contribution (weight w_i) to each component i. Further, each principal component i is associated with an *explained variance ratio* (EVR), which is the ratio of the variance of that component to the total variance, and it is denoted by v_i. EVR indicates the relative importance of each principal component. Then, we can define the importance of each band as follows:

$$value_j = w_{j1}\, v_1 + w_{j2}\, v_2 + \cdots + w_{jN}\, v_N, \tag{1}$$

REFERENCES

[1] Robert Allison, Joshua Johnston, Gregory Craig, and Sion Jennings. 2016. Airborne optical and thermal remote sensing for wildfire detection and monitoring. *Sensors* 16, 8 (2016), 1310.

[2] Hao Chen, Ye Zhang, Junping Zhang, and Yushi Chen. 2010. A BOI-preserving-based compression method for hyperspectral images. *IEEE Transactions on Geoscience and Remote Sensing* 48, 11 (2010), 3913–3923.

[3] Linsen Chen, Cc Dong, Du Chen, Han Li, Yuanyuan Zhao, Xun Cao, and Zhan Ma. 2017. Mobile Multispectral Video Streaming. In *Proc. of the Thematic Workshops of the ACM Multimedia Conference (MM'17)*. ACM, 126–134.

[4] Valerie C Coffey. 2012. Multispectral imaging moves into the mainstream. *Optics and Photonics News* 23, 4 (2012), 18–24.

[5] Chafik Egho and Tanya Vladimirova. 2014. Adaptive hyperspectral image compression using the KLT and integer KLT algorithms. In *In Proc. of the NASA/ESA Conference on Adaptive Hardware and Systems (AHS'14)*. IEEE, 112–119.

[6] Leyuan Fang, Nanjun He, Shutao Li, Antonio J Plaza, and Javier Plaza. 2018. A New Spatial-Spectral Feature Extraction Method for Hyperspectral Images Using Local Covariance Matrix Representation. *IEEE Transactions on Geoscience and Remote Sensing* (2018).

[7] C. Floridia, F. C. Salgado, J. B. Rosolem, F. R. Bassan, J. P. V. Fracarolli, R. S. Penze, and L. M. Pereira. 2016. Methane leak detection and spectral analysis by using only optical time domain reflectrometry in semidistributed remote optical sensors. In *2016 IEEE SENSORS*. 1–3. https://doi.org/10.1109/ICSENS.2016.7808684

[8] Wei Fu, Shutao Li, Leyuan Fang, and Jón Atli Benediktsson. 2017. Adaptive spectral–spatial compression of hyperspectral image with sparse representation. *IEEE Transactions on Geoscience and Remote Sensing* 55, 2 (2017), 671–682.

[9] Vinay Kumar and JK Ghosh. 2017. Camouflage Detection Using MWIR Hyperspectral Images. *Journal of the Indian Society of Remote Sensing* 45, 1 (2017), 139–145.

[10] M. Lahlimi, M. A. Kerroum, and Y. Fakhri. 2017. Band selection with the Bhattacharyya distance based on the Gaussian mixture model for hyperspectral image classification. In *2017 International Conference on Electrical and Information Technologies (ICEIT)*. 1–6. https://doi.org/10.1109/EITech.2017.8255282

[11] Astha Puri, Ershad Sharifahmadian, and Shahram Latifi. 2014. A comparison of hyperspectral image compression methods. *International Journal of Computer and Electrical Engineering* 6, 6 (2014), 493.

[12] D. M. Tratt, K. N. Buckland, E. R. Keim, and P. D. Johnson. 2016. Urban-industrial emissions monitoring with airborne longwave-infrared hyperspectral imaging. In *2016 8th Workshop on Hyperspectral Image and Signal Processing: Evolution in Remote Sensing (WHISPERS)*. 1–5. https://doi.org/10.1109/WHISPERS.2016.8071711

[13] Philippe Lagueux Alexandre VallièÃÍres AndrÃĬ Villemaire Jean Giroux Vincent Farley, Martin Chamberland. 2007. Chemical agent detection and identification with a hyperspectral imaging infrared sensor. *Proc.SPIE* 6661, 6661 – 6661 – 9. https://doi.org/10.1117/12.736731

[14] J. Wang, X. Wang, K. Zhang, K. Madani, and C. Sabourin. 2018. Morphological Band Selection for Hyperspectral Imagery. *IEEE Geoscience and Remote Sensing Letters* 15, 8 (Aug 2018), 1259–1263. https://doi.org/10.1109/LGRS.2018.2830795

[15] J. Wang, K. Zhang, P. Wang, K. Madani, and C. Sabourin. 2017. Unsupervised Band Selection Using Block-Diagonal Sparsity for Hyperspectral Image Classification. *IEEE Geoscience and Remote Sensing Letters* 14, 11 (Nov 2017), 2062–2066. https://doi.org/10.1109/LGRS.2017.2751082

[16] Qi Wang, Jianzhe Lin, and Yuan Yuan. 2016. Salient band selection for hyperspectral image classification via manifold ranking. *IEEE transactions on neural networks and learning systems* 27, 6 (2016), 1279–1289.

[17] Arif Kurnia Wijayanto, Octo Sani, Nadia Dwi Kartika, and Yeni Herdiyeni. 2017. Classification Model for Forest Fire Hotspot Occurrences Prediction Using ANFIS Algorithm. In *IOP Conference Series: Earth and Environmental Science*, Vol. 54. IOP Publishing, 012059.

[18] Ying Zhan, Dan Hu, Haihua Xing, and Xianchuan Yu. 2017. Hyperspectral Band Selection Based on Deep Convolutional Neural Network and Distance Density. *IEEE Geoscience and Remote Sensing Letters* 14, 12 (2017), 2365–2369.

[19] F. Zhang, Q. Wang, and X. Li. 2017. Hyperspectral image band selection via global optimal clustering. In *2017 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*. 1–4. https://doi.org/10.1109/IGARSS.2017.8126818

[20] Gong Li Zhang, Ma and Liu. 2017. Memetic algorithm based feature selection for hyperspectral images classification. *IEEE Congress on Evolutionary Computation* (2017).

[21] Jing Zhang and Guizhong Liu. 2007. Hyperspectral images lossless compression by a novel three-dimensional wavelet coding. In *Proc. of the ACM Multimedia Conference (MM'07)*. ACM, 759–762.

[22] Ma Zhang and Gong. 2017. Unsupervised Hyperspectral Band Selection by Fuzzy Clustering with Particle Swarm Optimization. *IEEE Geoscience and Remote Sensing Letters* 14, 5 (2017), 773–777.

[23] Zilong Zhong, Jonathan Li, Zhiming Luo, and Michael Chapman. 2018. Spectral–Spatial Residual Network for Hyperspectral Image Classification: A 3-D Deep Learning Framework. *IEEE Transactions on Geoscience and Remote Sensing* 56, 2 (2018), 847–858.