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Compact spectral camera with deep learning-enabled spectrum decoding

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Abstract: We present a compact system for capturing spectral images with low cost and miniaturized setup. The system is capable of effectively decoding three-dimensional data across 450 spectral channels without requiring any pre-collimation.

1. Introduction

Spectral imaging has become an indispensable tool in various fields, including environmental monitoring [1], medical diagnostics [2] and remote sensing [3], due to its ability to capture both spatial and spectral information from a scene.

Traditional spectral imaging systems, such as those based on dispersive optics or filter wheels, often suffer from high complexity, bulky size, and high cost, making them unsuitable for portable or low-cost applications [4]. More recent developments in snapshot spectral imaging like Coded aperture snapshot spectral imaging (CASSI) [5] have demonstrated improved light efficiency through compressive sensing paradigms, yet these systems often require complex optical alignment procedures and specialized coding elements that increase implementation complexity and production expenses.

In this work, we present a novel integrated, miniaturized, and low-cost spectral imaging camera that addresses these challenges. Our design features an optimized micro-filterwheel assembly achieving 90% volume reduction compared to conventional implementations, coupled with a cost-effective spectral encoding component (production cost less than USD 0.1). The proposed system utilizes a multi-layer perceptron (MLP) network to perform efficient and accurate decompression of the encoded data, enabling the reconstruction of a hyperspectral image stack with 450 spectral channels. This integration of miniaturized hardware design with efficient neural network processing establishes a new framework for developing high-performance spectral imaging systems suitable for portable and cost-sensitive applications.

2. Methods and experiments

The setup of our system used in the experiment is shown in Fig. 1. The optical configuration comprises a target scene imaged through a compound lens system consisting of an objective lens and a relay lens. A custom-designed spectral encoding filter (thickness 0.3 mm, 10×10 mm active area) made up of colorful Polyvinyl Chloride (PVC) films is positioned at the image plane between the objective lens and relay lens. This filter implements wavelength-dependent spatial modulation through its spectral transmission profile. After the encoding process, the spatially modulated image is projected onto a monochrome CMOS sensor (MV-CB120-10UM-C), which serves as the detection element. The sensor captures the encoded images containing both spatial and spectral information.

The MLP network was trained on a synthetically generated dataset comprising 15,000 spectral profiles spanning 350 nm - 800 nm with 1 nm resolution (451 spectral bands per pixel). Each spectrum was paired with ten corresponding compressed values generated through our optical encoder's transmission model. The dataset was partitioned into training (9,600 samples), validation (2,400 samples), and test sets (3,000 samples), maintaining an approximate 64:16:20 ratio to ensure statistical robustness. The reconstruction MLP processed 10 encoded inputs through five hidden layers (64-128-256-128-64 nodes, ReLU activation) to output 451 spectral channels via sigmoid-activated predictions.

3. Results and discussion

Figure 2 illustrates the training results of the model. The left panel shows the training and validation loss curves, demonstrating the convergence and stability of the model during training. The right panel compares the reconstructed spectrum (red line) with the ground truth (dashed line), where the green dots represent the corresponding

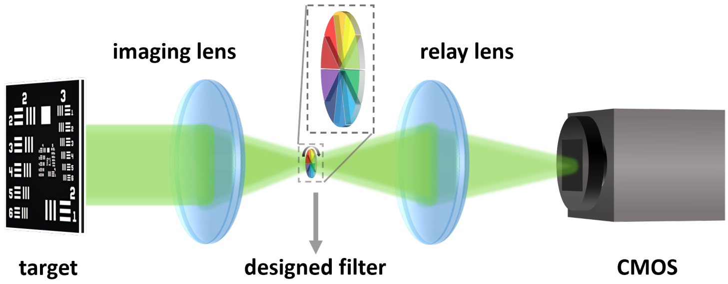

Fig. 1: Setup for our proposed compact 450-channel hyperspectral imaging system.

10 encoder values used for reconstruction. The close agreement between the reconstructed and reference spectra validates the system's ability to recover high-resolution spectral features from compressed measurements. Quantitatively, the reconstruction achieves a mean squared error (MSE) of 0.010030 and a peak signal-to-noise ratio (PSNR) of 19.98 dB.

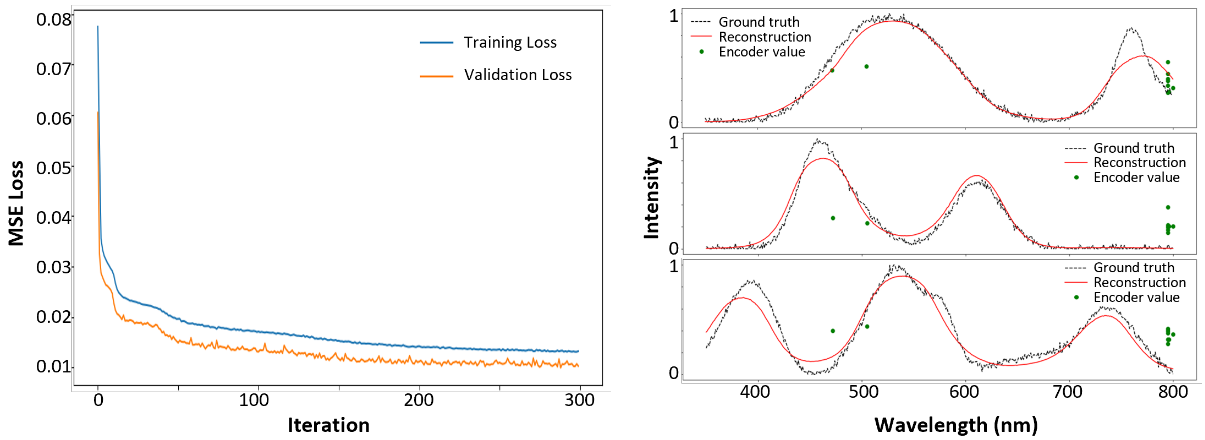

Fig. 2: Model convergence and spectral reconstruction performance: training and validation loss curves (left) and comparative visualization of reconstructed spectra (red line) against ground truth (dashed line) under varying noise conditions (right).

The proposed system's combination of low-cost hardware and advanced machine learning-based reconstruction offers a scalable solution for various applications where portability, affordability, and ease of use are critical. This paper details the system design, encoding and decoding methodology, and experimental results, demonstrating the capability of our approach to achieve high-quality spectral imaging with minimal hardware requirements. By bridging the gap between performance and cost, this work opens new avenues for the practical deployment of spectral imaging in resource-constrained settings.

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