Low Cost Hyperspectral Imaging Using Deep Learning Based Spectral Reconstruction

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I. Introduction

Hyperspectral Imaging (HSI) has in recent decades moved away from typical remote sensing applications to industry focused or medical applications, generating a demand for more cost effective and mobile devices. Recent research focus was put towards Multispectral Imaging (MSI) systems that are able to recover HSI data. In [1], an MSI system based on time multiplexed illumination using Light Emitting Diodes (LED) is proposed using 17 wavelengths. These wavelengths show good coverage of the spectral range form 450 - 990 nm but lack a generic solution to all problems. In [2], an MSI camera based on LEDs was proposed that is able to recover HSI data from 370 - 1630 nm knowing the exact spectral sensitivity of the camera system and the radiance of the illumination. HSI recovery from consumer grade RGB images was proposed in [3] using a sparse dictionary generated from HSI prior. The reconstruction showed good performance for natural scenes but also requires knowledge about the spectral sensitivity of the camera and is limited to the use of RGB images. A more generic way of reconstructing HSI data can be achieved employing the emerging field of deep learning. In [4], a reconstruction algorithm based on Neural Networks (NN) was proposed that can recover cutaneous data. The system however relies on a filter wheel and has therefore expensive, cumbersome mechanics. Inverse problems such as reconstructing high dimensional data from lower dimensional features have in recent years successfully been solved with deep learning [5], which lead us to propose a very low cost MSI system that can reconstruct HSI data using deep learning efficiently and without any prior spectral knowledge of the MSI system.

II. Hardware architecture

The MSI camera system shown in Figure 1 comprises a monochromatic digital camera whose image integration is synchronised via an Arduino with a ring of 24 WS2812B RGB LEDs all radiating the same colour at a time, realising time multiplexed MSI acquisition. The data acquisition is done with a Single Board Computer making the device fully mobile, lightweight and low cost (less than GBP 1000). The CIE 1964 colour matching function is used to approximate according wavelengths with RGB lights. It has to be mentioned that these wavelengths are only approximations as factors such as ambient lighting, peak wavelengths of the LEDs and camera

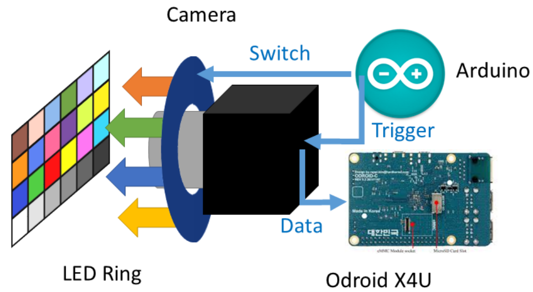

Fig. 1. Architecture of MSI camera system

sensitivity have an effect on the actual wavelengths recorded and not all wavleengths can be generated using only RGB sources. The camera has a frame rate of 200 fps and the rate of image cubes is dependent on the number of chosen channels. We are recording 1 up to 11 channels allowing for frame rates between 200 and 18 fps for MSIs.

III. Hyperspectral reconstruction

Reconstruction of HSI data from MSI images is done using a deep NN. Hyperspectral signatures of known image objects need to be available and matched with data collected with the MSI camera. A neural network is designed that matches an input matrix $\mathbf{X} = \{\mathbf{x}_1, ..., \mathbf{x}_m\}^T$ of MSI vectors $\mathbf{x}_i$ to an output matrix $\mathbf{Y} = \{\mathbf{y}_1, ..., \mathbf{y}_m\}^T$ of HSI vectors $\mathbf{y}_i$ through four fully connected (FC) hidden layers $\mathbf{x}_{i+1} = \sigma_i(\mathbf{W}_i\mathbf{x}_i+\mathbf{b}_i)$ with activation functions σ_i, weight matrices $\mathbf{W}_i$ and bias $\mathbf{b}_i$. The architecture of the network is shown in detail in Figure 2. For training, we define the network as a loss function $\mathcal{J}(\Theta)$ with $\Theta = \{\mathbf{W}_1, ...\mathbf{W}_i, \mathbf{b}_1, ..., \mathbf{b}_i\}, i \in \{1...5\}$. For the estimated output $\hat{\mathbf{Y}}$, the loss function is defined as

$$\mathcal{J}(\Theta) = \frac{1}{2m}||\mathbf{Y} - \hat{\mathbf{Y}}||_F + \frac{\beta}{2}\sum_{i=1}^{5}||\mathbf{W}_i||_F \qquad (1)$$

where $||.||_F$, denotes the Frobenius norm and β is a weight parameter for the regularisation term. Regularisation is introduced to prevent over-fitting and premature convergence. This is particularly important because the input dimensionality will be significantly less than the output dimensionality. As a results, small variations in the input can have a significant effect on the estimation and the network needs to be able to generalise. As seen in Figure 2, the input layer has no

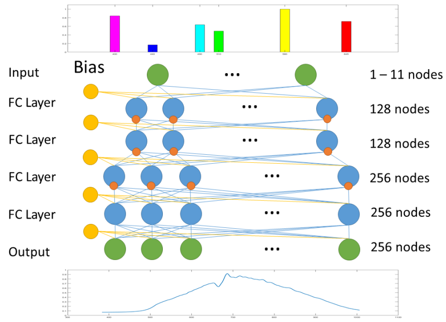

Fig. 2. Design of neural network for HSI reconstruction. Orange circles indicate Sigmoid activation functions.

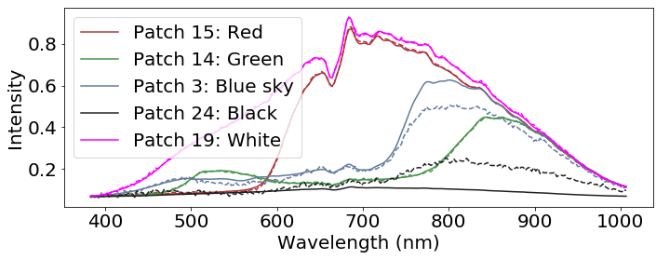

Fig. 3. Visualisation of the reconstructed Macbeth chart patches for red, green, blue sky, white and black. Solid lines indicate the original HSI data and dashed lines the respective reconstruction.

additional activation function to enforce the usage of all input nodes for this very reason. The last hidden layer also has no activation function as this has proven to generalise better for all spectra.

IV. Experimental Results

Reconstruction was tested on the Macbeth colour checker chart that has 24 patches with known spectra. It was imaged with a HSI system (400 - 950nm) on 256 bands to generate the ground truth and the proposed camera using 11 channels between 400 and 700 nm spaced at 25nm. A varying number of equally spaced channels across that range were used and 4000 pixels of each patch were used to train the NN over 50 000 iterations and the same amount was used for testing repeated five times each. Results for the overall Root Mean Squared Error (RMSE) of the reconstruction can be seen in Figure 4. One can see that with 5 channels, most spectra can correctly be reconstructed. Table I shows the individual reconstruction error for each colour patch using 5 channels and 50 000 iterations. A few selected spectra are plotted in Figure 3 to visualise the error. It can be seen that most errors occur for darker patches, because the initial signal is weaker, i.e. has a lower signal-to-noise ratio. Additionally, wavelengths above 650 show more errors, especially for the darker patches. This is likely due to the fact that the MSI system does not cover this spectral region and is therefore not able to pick up according features.

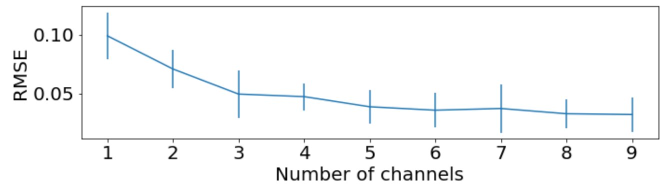

Fig. 4. Reconstruction error for varying number of channels used.

TABLE I
RECONSTRUCTION RMSE OF THE INDIVIDUAL PATCHES ON THE MACBETH CHART. EACH CELL INDICATES THE CORRESPONDING PATCH ON THE CHART.

0.012	0.011	0.045	0.011	0.013	0.016
0.008	0.007	0.007	0.006	0.007	0.005
0.004	0.005	0.005	0.005	0.005	0.003
0.005	0.021	0.045	0.072	0.095	0.067

V. Conclusion

We have proposed a low cost MSI system that is able to reconstruct spectral signatures from HSI prior using deep learning. RGB LEDs make the camera system flexible in terms of utilised channels that can be adjusted to specific application requirements. The reconstruction can work with input data of any dimensionality without a-priori information about the spectral configuration of the MSI data. With only 5 channels, a good reconstruction was achieved allowing for an acquisition rate of 40 MSI images per second. The disadvantage of the system is the requirement for HSI prior with according ground truth information. The imaging also requires a controlled environment as it is illumination dependent and objects should ideally be placed no more than 20 - 30 cm away from the illumination source. Future work may include testing the reconstruction on naturally occurring materials, using LEDs with a wider spectral range as well as more research into the design and optimisation of neural networks for an optimal reconstruction with good qualities for generalisation.

References

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