RETRIEVING SINGLE SCATTERING ALBEDOS AND TEMPERATURES FROM CRISM HYPERSPECTRAL DATA USING NEURAL NETWORKS. L. He[1], R. E. Arvidson[2] and J. A. O'Sullivan[1], [1]Preston M. Green Department of Electrical and Systems Engineering, Washington University in St. Louis, St. Louis, MO, USA 63130, [2]Department of Earth and Planetary Sciences, Washington University in St. Louis, St. Louis, MO, USA 63130

Introduction: The Compact Reconnaissance Imaging Spectrometer for Mars (CRISM) on the Mars Reconnaissance Orbiter began acquiring hyperspectral images from 0.362 to 3.92 µm in 2006 [1]. The long wavelength portion of the data have radiative streams that include both solar and thermal terms from the surface and atmosphere. We use the DISORT radiative modeling code to simulate both solar and emission radiative streams, predicting spectral radiance and IOF (radiance/solar radiance) on sensor. We use a neural network (NN) approach to simultaneously retrieve surface spectral single scattering albedos and temperature maps. The NN is trained with numerous laboratory-based spectra chosen to represent the range of possible soils and rocks on Mars, together with use of DISORT outputs that cover a range of SSA and surface temperature values. This approach alleviates the need to assume that any given Martian spectrum is a linear combination of dark and bright area spectra [2][3]. Further, DISORT treats solar surface radiative streams as bidirectional and emission streams as directional hemispherical values for modeling surface SSA spectra, and surface temperatures, gases, and dust and ice opacities. DISORT mapping is implemented as a look-up table with interpolations so it is challenging to retrieve unique temperature and SSA spectra for each pixel.

NN design: *Input and output design.* For NN processing we utilize 491 nodes and for each CRISM scene we input IOF data from 1.4 to 3.85 µm (320 bands), SSA spectra from 1.4 to 2.5 µm (169 bands), which can be uniquely retrieved from the DISORT-based look-up table between IOF and SSA value because temperatures are not relevant in this wavelength region. We aim to estimate single scattering albedo at longer wavelengths and surface temperatures. Therefore 152 nodes with SSA data from 2.5 to 3.9 µm (called SSA_post in Fig. 1), and estimated temperatures are designed as outputs of the NN.

Hidden layers and nodes. According to Funahashi [4] and Hornik [5], any continuous function on a bounded interval can be approximated by a single hidden layer neural network. It is reasonable to assume the inverse of the DISORT look-up table is a continuous function, therefore we use a one layer NN (in Fig. 1). We design the number of hidden nodes as equal to the number of inputs, which is 491. The activation function is chosen as reLU defined as $f(x) = \max(0, x)$ for all hidden nodes, therefore unknown parameters for this NN are the weights on the edges.

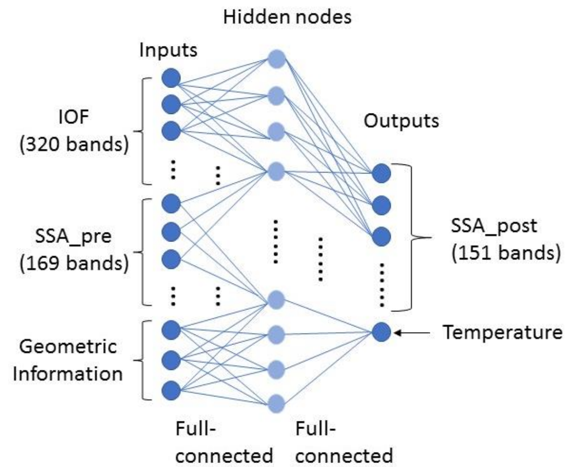

Fig. 1. Flow chart of designed Neural Network.

Dataset. Mars analog laboratory spectral data are used to train the unknown weights in our NN. Because there are~300,000 unknown weights, 300,000 training examples are generated. Each training example contains one lab-based SSA spectrum or combinations of these spectra (320 bands), one temperature, three geometric parameters, and a corresponding IOF cube (320 bands) generated from the DISORT model. SSAs are randomly chosen from the laboratory spectra, temperatures are randomly generated using a reasonable range, and geometric parameters are chosen for each pixel in a scene. We assume that we know the SSA spectral data for 1.4 to 2.5 µm, because, as noted there is a unique mapping from IOF to SSA, i.e., there are no temperature effects at Martian surface temperatures (~230 to 300 K).

Training. To train the NN we estimate the 2.5 to 3.85 µm SSA spectra and temperature for each pixel and compare these to input values, using a backpropagation method (shown in Fig. 2) to minimize the sums of squares of deviations between actual and predicted values. The result is a NN tuned to estimate SSA spectra and temperatures for pixels for each scene. Regularization is needed to avoid NN over-fitting of the training set. An L-2 norm regularization is used and the regularization weight is chosen by cross validation.

Performance analysis: We test our performance for CRISM scene FRS00028346 covering the Curiosity Mars rover landing site and traverse locations.

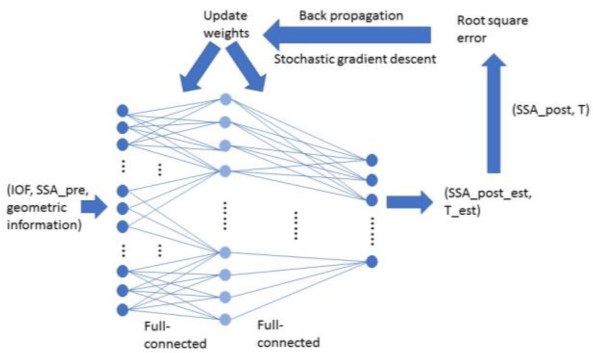

Fig. 2. Backpropagation flow chart.

Predicted Temperature Errors. To explore the sensitivity to temperature predictions we generated a test data set of SSA spectra, trained the NN, and ran the procedure to estimate SSA and temperatures. The average training and test errors are both around 1.3 K for this scene for temperature range 260~285 K. Our NN approximates the inverse of DISORT mapping well.

Real data. The IOF cube for FRS00028346 in Fig. 3 covers Hummocky Plains (brighter area) and part of the Bagnold Dune (darker area) within Gale crater. The temperature mapping from NN for this scene is shown in the bottom of Fig. 4. Another temperature mapping from a thermal model [5] shown in the top of Fig.4 has been calibrated using Curiosity's Remote Environment Monitoring Station (REMS) surface temperature (268 K [6]) of Hummocky Plains in Fig 4. The NN estimate is 268.8 K, which is very close to the measured temperature. Moreover, the NN temperature mapping matches the pattern of the thermal model (Dune Field is warmer than Hummocky Plains). SSA spectra are shown in Fig. 5, retrieved from Dune Field and Hummocky Plains (Fig. 4). The spectra of the Hummocky Plains retrieved from the model and NN-based temperatures are similar for both estimates due to similar temperature estimates. The NN-based spectrum for the Dune Field is different than the one retrieved from the model temperature, likely because the model temperature was estimated at hundred meter scales. The NN estimate is based on 18 m scales and captures more of the sun-facing dune surfaces in this afternoon scene.

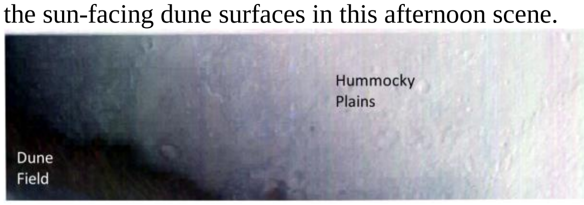

Fig. 3 IOF sensor space cube for FRS00028346 shown in RGB with 1.401 μm, 1.994μm and 2.510 μm.

Future work: 1. We have focused on generating a NN with the corresponding regularization weight to approximate the inverse of DISORT mapping for one scene (fixed atmosphere parameters). In the future, we plan to broaden the scope of the training data to include multiple scenes. 2. We also plan to apply the NN approach to Mars Express Observatoire pour la Mineralogie, l'Eau, les Glaces et l'Activite (OMEGA) [7] data. OMEGA covers ~0.5 to 5.2 μm and the longer wavelengths should provide an excellent way to separate SSA and temperatures. Plans include cross-comparison of CRISM and OMEGA results for the same areas and times.

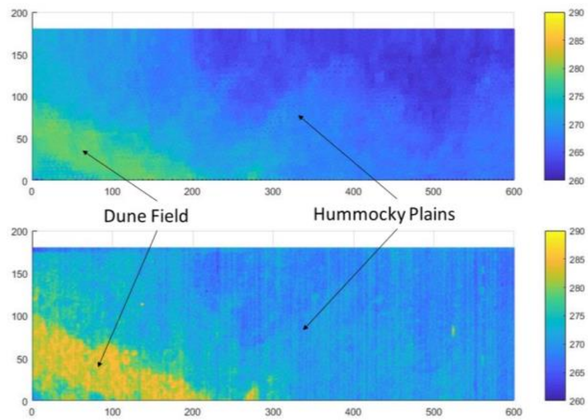

Fig. 4 The top is a sensor space temperature map from the thermal model and the bottom is from the NN. The colorbars in the right show temperature range in Kelvin. Curiosity landed in the area shown at the end of the Hummocky Plains arrow.

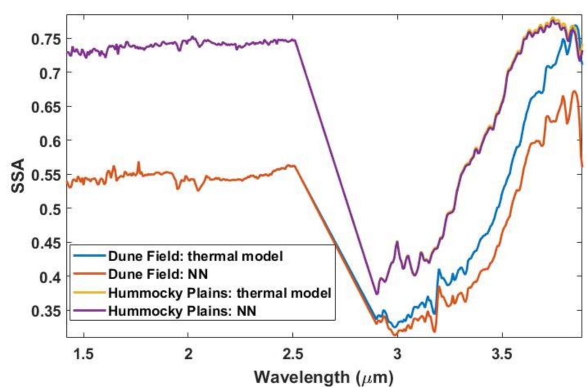

Fig. 5 SSAs retrieved from Dune Field and Hummocky Plains in Fig. 4 for different temperature estimates.

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