Maximum Log-likelihood Method with Weighting Penalty for CRISM Hyperspectral Images. L. He¹, R. E. Arvidson², J. A. O’Sullivan¹, and D. V. Politte¹, 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 (MRO) is a push-broom hyperspectral imaging spectrometer from 362 to 3920 nm with 6.5 nm spectral band spacing and the smallest ground pixel size of 18 m. Since 2010, images have also been acquired using a gimbal along track oversampled (ATO) mode, with significant pixel overlapping in the along-track direction. The overlap allows reconstruction of map-projected images with 9 to 12 m/pixel, depending on the degree of overlap. For reference CRISM operates as S (362 to 1030 nm) and L (1036 to 2650 nm) imaging spectrometers. Our original log maximum likelihood method (MLM) for CRISM data [1] is improved by introducing new weighting penalties in both the spatial and spectral domains.

Initial Processing: Two processing steps are necessary before application of the MLM procedures [1]: 1. Retrieval of Single Scattering Albedos (SSAs) and 2. Extrema removal using a median filter. SSA is the ratio of scattering efficiency to scattering plus absorption efficiencies of a single particle. After dividing by the solar spectral radiance at Mars at the time of the observation, Discrete Ordinates Radiative Transfer (DISORT)-based processing, and the Hapke function for surface scattering are used to retrieve SSA values [1]. A median filter (bit error filter) designed by Elison and McEwen [2] is utilized for noisy scenes to remove extreme noise spikes in the L data because of degraded cooler operation, and introduction of time and space variable responses within the 2D detector array [1,3].

Maximum Log-likelihood Method: Positive SSA values $d_1, d_2, \ldots, d_N \in \mathbb{R}_+$ are in sensor space and the intent is to reconstruct the best nonnegative cube $c_1, c_2, \ldots, c_M \in \mathbb{R}_+$ projected onto the surface, and the best estimate cube in the sensor space $\lambda_1, \lambda_2, \ldots, \lambda_N \in \mathbb{R}_+$. Based on the hypothesis testing by Kreisch et al. [1], the resultant SSA $d_i$ are well modeled by the Poisson distribution with parameter $\lambda_i$. We assume the mapping between the projected image and the best estimate is linear with a known Gaussian kernel $h_j$, that is, $\lambda_i = \sum_j h_j c_j$. Since maximizing the log-likelihood for a Poisson distribution is equivalent to minimizing the I-divergence between $d_i$ and $\lambda_i$, $I(d_i \parallel \lambda_i) = d_i \ln \frac{d_i}{\lambda_i} - d_i + \lambda_i$, the reconstruction could be described as the optimization problem:

$$
\min_{c_1, \ldots, c_M} \sum_{i=1}^{N} I(d_i \parallel \lambda_i) + \Phi(c_1, \ldots, c_M)
$$

s.t. $\lambda_i = \sum_j h_j c_j$

where the penalty $\Phi(c_1, \ldots, c_M)$ is introduced due to the problem being ill-posed.

$\Phi(c_1, \ldots, c_M) = \Phi_1(c_1, \ldots, c_M) + \Phi_2(c_1, \ldots, c_M)$

$$
\Phi_1 = \sum_j w_{1,j} \sum_{i \in NA(c_j)} f(c_j, c_k, \beta_1, \delta_1)
$$

$$
\Phi_2 = \sum_j w_{2,j} \sum_{i \in NE(c_j)} f(c_j, c_k, \beta_2, \delta_2)
$$

$$
f(c_j, c_k, \beta, \delta) = \beta \delta^2 \log \cosh\left(\frac{c_j - c_k}{\delta}\right)
$$

where $\Phi_1, \Phi_2$ are the spatial and spectral regularizations and $NA(c_j), NE(c_j)$ are the spatial and spectral neighborhoods. The weights $w_{1,j}, w_{2,j}$ standing for spatial and spectral weights matter to our problem.

Spatial weights. Our previous approach [1] for incorporating the penalty functions used constant weights $w_{1,j} = 1$ for all pixels and bands, producing artifacts in the resulting images. Row artifacts were produced spatially because the penalty term was weighted higher than the I-divergence in undersampled areas, resulting in over-smoothing. Given the spatial transfer function, we compute the total contribution of each pixel in the projected image space to all data in the sensor space. This is the sensitivity image (shown in Fig. 1). Values in the sensitivity image can range over 20 orders of magnitude due to along-track oversampling variations. Making the weights in the spatial penalty proportional to the sensitivity values equalizes the relative importance of the I-divergence and penalty terms, and eliminates the row artifacts associated with high degrees of undersampling.

Spectral weights. The CRISM 2D detector array is subject to numerous noise sources that vary with wavelength, position on the detector, and time. The spectral
noise variations with wavelength comprise important noise elements and are quantified for the entire scene using a log-spectrogram (Fig. 2). The high frequency information is then scaled by a monotonically increasing concave function to compute the spectral weights \( w_{2,j} \), i.e., the magnitude of the spectral penalty depends on the noise level, with higher penalties associated with noisier wavelength intervals.

Fig. 1 The sensitivity image of scene FRT000013D1F. The brighter the area the higher the degree of oversampling between rows as CRISM collects data along track.

Fig. 2 Mean spectrogram of scene FRT000013D1F L data (without despiking) is shown with color-coded relative noise levels. The vertical axis is the spectral Fourier frequency. The power in time-spectral bins is displayed within a range \( 10^{-6.4} \sim 10^{-4.4} \).

**Performance Analysis:** FRT000013D1F L data is illustrative of results (Fig. 3). The spectral comparison between the MLM procedure and the standard projection is shown in Fig. 4.

Fig. 3 Projected scene at 12 m/pixel after MLM procedure overlain onto a Context Imager image. The spectral comparisons in Fig. 4 are derived from three locations labeled A, B, C.

Fig. 4 The spectral comparisons between the MLM reconstruction and the standard projection for three locations in Fig. 3. The regularized MLM procedure generates smoothed spectra following realistic absorption features.

**References:**