**FOCAL PLANE TEMPERATURE PREDICTION FOR THE LUNAR RECONNAISANCE ORBITER NARROW ANGLE CAMERA.** P. Mahanti<sup>1</sup>, T. Tran<sup>1</sup>, M. Tschimmel<sup>1</sup>, M. S. Robinson<sup>1</sup>, D. Humm<sup>2</sup>,LROC Team<sup>1</sup>. <sup>1</sup>School of Earth and Space Exploration, Arizona State University, Tempe, AZ, 85281, <sup>2</sup>SPICACON, Annapolis, MD, 21401

Introduction: The Lunar Reconnaissance Orbiter Camera (LROC) is acquiring images of the Moon with angular resolutions of 0.5 m to 2.0 meters per pixel [1]. The quality of Narrow Aangle Camera (NAC) images is affected by the focal plane temperature, which varies significantly (approximately 14 to 26 degrees) over the course of a lunar year. We developed a smooth adaptive prediction model for the focal plane temperature based on biharmonic splines. The model is found to be efficient from its current performance and is seen to adapt efficiently to observed temperature variation trends.

Temperature variations and NAC imaging: LROC consists of two NACs which employ Kodak KLI-5001G CCD detectors. Pixels are double-sampled on the CCD and shifted to low-noise, unity-gain amplifiers on the focal plane array after which amplification, analog-to-digital (A/D) conversion, 12-bit to 8-bit companding, and compression is applied before data downlink. The offset electronic charge (dark level) in the focal plane array is highly temperature dependant. If the dark level drops below zero counts, low signal regions, such as shadowed craters, are pegged at zero and have no detail. If the dark level is too high, the 12bit to 8-bit compression used for downlink to Earth is adversely affected. In count space, the 8-bit counts densely sample the 12-bit counts at low count levels, and sparsely sample the 12-bit counts at high count levels, where detector shot noise is high. However, if the dark level is too high, low signal areas of the image are sparsely sampled by the 12-bit to 8-bit conversion, even though the low signal areas have relatively low shot noise, resulting in over-quantization of low signal areas.

Requirement for temperature prediction: The lunar space environment is thermally challenging due to the lack of air cooling the electronics, and variation in thermal input from the Sun and Moon. The dark level of the NAC detector array changes significantly with detector array temperature in flight. This background sensitivity can be mitigated by commanding a temperature dependent dark level offset (reverse potential) for each image, but the dark level offset must be determined in advance and uplinked to the spacecraft well before each image is taken. Thus accurate prediction of the focal plane array temperature is vital for the highest quality imaging.

## Spacecraft position and focal plane temperature:

For a spacecraft in lunar orbit the gain or loss of heat on a spacecraft instrument is mainly due to three factors: a) direct solar radiation, b) lunar IR radiation, and c) lunar albedo [2]. In our instrument thermal model, the dominant source of temperature variation is assumed to be lunar IR. However all the major factors that drive the temperature change of a spacecraft in lunar orbit depend on the position of the spacecraft within the orbit (orbit position angle  $\theta$ ), the position of the orbital plane with respect to the Sun (beta angle  $\beta$ ), and the altitude of the spacecraft from the lunar surface (A). Since the orbit is not perfectly circular the orbit altitude varies with the orbit position angle. Thus, the temperature can be modeled with only 2 parameters if the altitude does not fluctuate much in a specific mission phase. This dependency is represented by:

$$T = f(\beta, \theta) \tag{1}$$

## Temperature parametric potential function model-

ing: We can model the NAC focal plane temperature as a potential function because the lunar orbital environment is at equilibrium with the lunar surface temperature. For both parameters the variations are smooth and thus the function surface can be assumed to be smooth and differentiable. The isotropic heat diffusion equation in 3-dimensional space gives us the temperature variation, the solution to which is a parametric harmonic function. Also, in general, the temperature around a body emitting IR is a harmonic function with no sharp edges. The function modeled in (1) is thus intuitively a harmonic function. The temperature model is thus smooth with no sudden changes. Our prediction model is dependent on extrapolation of trends found in the immediate past real flight data.

Usage of biharmonic splines for extrapolation of flight data: In order to model a function that is harmonic and from the property that any harmonic function is bi-harmonic it is expected that our underlying harmonic function would be effectively modeled by a bi-harmonic spline model which is given by

$$\nabla^4 f = 0 \tag{2}$$

Important advantages of using the bi-harmonic spline apart from above are that it uses fewer model parameters, works fine for irregularly spaced data points and follows the minimum curvature property, leading to better data fitting. Green functions of the bi-harmonic operator in two dimensions are used for interpolation

and extrapolation purposes [3]. So the temperature distribution is modeled as a linear combination of Green functions. The generalized model is thus

$$w_i = \sum_{j=1}^{N} \alpha_j \varphi_m(x_i - x_j)$$
 (3)

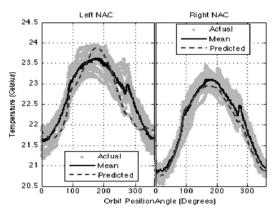
Where w are the N temperature data points, x's are the 2D parametric positions ( $\beta$  and  $\theta$ ) and  $\alpha$ 's are the model parameters we intend to find. The Green function  $\phi_m$  for 2D is given by

$$\varphi_m = |x|^2 \left( \ln(x) - 1 \right) \tag{4}$$

The model represents an over-determined system of equations whose parameters are found by least-square minimization.

$$\underset{\alpha}{\operatorname{arg\,min}} = \sum_{i=1}^{N} \left| w_i - \sum_{j=1}^{N} \alpha_j \phi_m(x_i - x_j) \right|^2 \tag{5}$$

Once the parameters are known we know the linear combination of the functions generating the temperature surface and can use this to interpolate and extrapolate at unknown values in least-square sense. We have thus a surface optimally fitted to flight data which we extend to predict future values. Owing to the nonlinearity, we adopt the policy of 'predict forward as we learn'. This means that with existing data, we predict temperature values only a few days forward and update the model with actual observed data as we go along. In our process of prediction, it is always maintained that the interpolation is good and the extrapolation is always based on maximum knowledge of trends.



**Fig. 1**. Data and results for day of year 267.

**Prediction results and performance analysis:** The prediction model was found to work satisfactorily during all the phases of the mission so far. We analyze the performance in the root-mean-squared (RMS) error sense. As can be seen in Fig.1, the predicted temperature is able to capture the trend as the orbit angle changes during a day.

The prediction with respect to change in beta angle is shown in Fig.2 where we plot the mean temperature predicted for 105 days and the actual temperature.

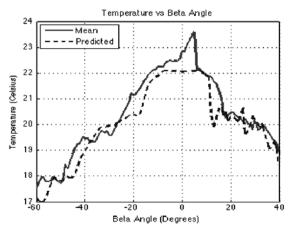
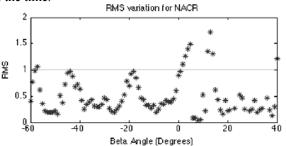


Fig. 2. Mean and Predicted values for Right NAC.

The restriction in the temperature variation of image DN's is the ultimate goal of the whole exercise. For the LROC NAC this variation with temperature (T) is

$$\Delta DN \cong 10\Delta T \tag{6}$$

Since, the maximum DN is 4096, temperature variations of the order of 1 degree cause negligible image quality change. Fig.3 shows that the RMS prediction error was less than 1 degree for a very high percentage of the time.



**Fig. 3**. RMS error (temperature) over 100° of beta. Predicted temperatures were rarely more than 1° from actual.

**Conclusion:** We have implemented a novel temperature prediction model for the LROC NAC focal plane temperatures which is presently working with an accuracy of 1°C. As a result the NAC images have optimal dark levels which help maximize signal-to-noise ratios.

**References:** [1] Robinson M.S. et al. (In Press) Space Sci. Review. [2] Gilmore D.G. (2002) Spacecraft Thermal Control Handbook: Fundamental Technologies, Aerospace Corp., 53-56 [3] Sandwell D.T. (1987) Geophys. Res. Lett., 14(2), 139–142.