DUST STORMS AND WATER ICE CLOUDS: FEATURE DETECTION FOR USE ONBOARD THEMIS. Kiri L. Wagstaff (kiri.wagstaff@jpl.nasa.gov), *Jet Propulsion Laboratory, Pasadena, CA 91109, USA*, Joshua L. Bandfield, *Department of Geology, Arizona State University, Tempe, AZ 85287, USA*, Rebecca Castaño, Steve Chien, *Jet Propulsion Laboratory, Pasadena, CA 91109, USA*, Michael D. Smith, *NASA Goddard Space Flight Center, Greenbelt, MD 20770, USA*.

Introduction: We are developing and testing data analysis algorithms that are destined for use onboard the Thermal Emission Imaging System (THEMIS), currently in Mars orbit on the Mars Odyssey spacecraft. In particular, these algorithms can detect thermal anomalies (which could be indicators of geothermal activity), track the movements of the seasonal polar caps [1], and detect dust storms and water ice clouds in the atmosphere. Performing data analysis onboard spacecraft will permit better use of instrument time and bandwidth, as recently demonstrated by the Autonomous Sciencecraft Experiment (ASE) onboard Earth Orbiting 1 (EO-1). This spacecraft can analyze scenes collected by the Hyperion instrument to determine when features of interest, such as lake ice breakup or volcanic eruptions, are present [2]. No such onboard analysis has yet been performed by spacecraft in Mars orbit.

In this abstract, we report on results obtained by our dust and water ice cloud detection algorithms when applied to raw data as it is collected by THEMIS. We compare these aerosol estimates to ground-based analyses of the fully calibrated THEMIS data by Smith et al. [3]. We find that both algorithms are, on average, able to estimate optical depth (τ) to within the same level of the uncertainty associated with the values computed by Smith et al. We conclude that these algorithms are performing at a level suitable for future use onboard THEMIS.

Estimating Aerosols in the Martian Atmosphere: In this work, we analyze THEMIS daytime infra-red (IR) images, which have a 100-m spatial resolution. THEMIS observations span nine wavelengths, from 6.78 to 14.88 μm. Each image is 320 pixels (32 km) wide and a variable number (3600 to 14352) of pixels long, divided into 256-line "framelets".

Smith et al. [3] developed a method for estimating the atmospheric dust and water ice optical depths using calibrated THEMIS data (bands 3-8). Their model relies on an estimate of the surface emissivity from concurrent TES observations. After analyzing data from February 2002 (L_s = 300°) to March 2003 (L_s = 161°), and evaluating their model on synthetic spectra, they determined that the uncertainty associated with their aerosol estimates was about 0.04 or 10% of the total optical depth, whichever is larger [3].

The purpose of this work is to determine how closely we can approximate the true optical depth values using only the raw data that is available onboard THEMIS. In particular, we do not make use of TES observations or any other source of information. However, we do apply a pseudo-calibration to the raw digital numbers DN_b, as follows: $T_b = M_b \times \ln(DN_b) - O_b$, where T_b is the calibrated value for band b, and M_b and O_b are constants determined empirically:

Band	2	3	4	5
M_b	231.82	86.02	49.52	45.42
O_b	914.11	167.28	-17.75	-38.43

Band	6	7	8	9
M_b	56.38	57.56	76.77	114.41
O_b	17.19	23.40	120.54	311.67

In the operational scenario we envision, scientists will be able to specify an optical depth threshold that defines events of interest (for example, a dust τ that exceeds 0.8). THEMIS will then identify any images that contain these interesting events and flag them for priority download. Flexibility in defining "interesting" is essential for events such as dust storms, since the minimum dust τ for what should be considered a "storm" event varies with the season.

Methods: We explored different methods for building a regression model that maps THEMIS observations at different wavelengths to the dust and water ice optical depth values as computed by Smith et al. In each case, we arbitrarily selected every 50th framelet observed by THEMIS for inclusion in a training set, from which we constructed our models. We evaluated the models over the entire data set (72,061 framelets). We also scaled the input data so that each band had a zero mean and unit standard deviation.

Each linear regression model that we constructed is of the form $\tau' = \beta + \sum_{b=2}^{9} w_b \times T_b$ where τ' is the predicted optical depth, an approximation of the true value τ. The inputs are THEMIS bands 2 through 9 (T_2 through T_9).

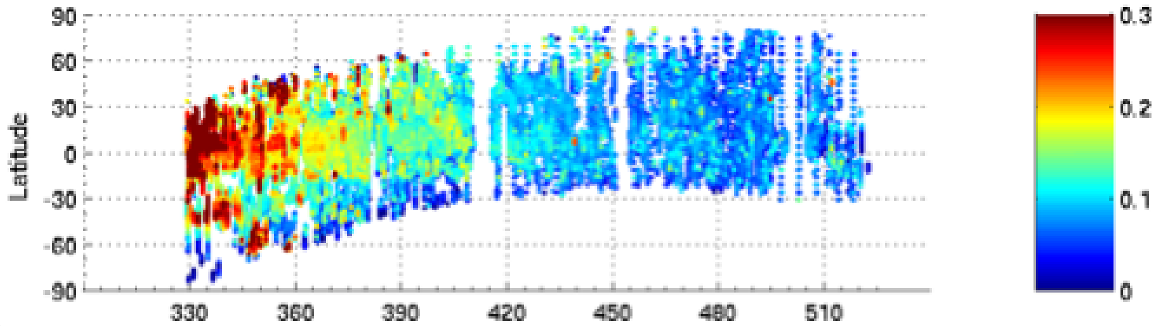
The simplest approach is to perform a linear least-squares regression, in which we estimate the coefficients β and w so as to minimize the sum of the squared errors between the true τ and the predicted τ':

$$\sum_i (\tau_i - \tau_i')^2 \tag{1}$$

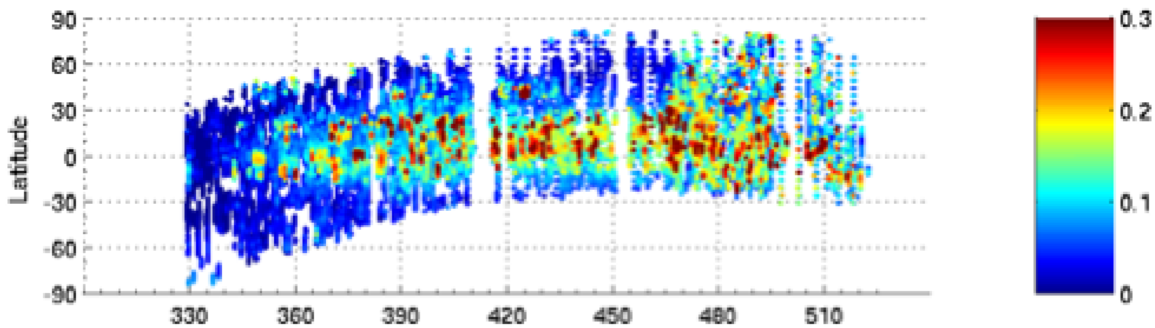
We also evaluated a support vector machine (SVM) regression model, which is a recently developed advance over neural networks [4]. This model attempts to trade off a linear fit to the data with a "flatness" bias that provides better generalization properties (to new observations). To do this, we minimize

$$\frac{1}{2}||w||^2 + C \sum_i (\max(|\tau - \tau'| - \epsilon, 0)) \tag{2}$$

in which C trades off the flatness bias (first term) with the closeness of fit to the data (second term). β is solved for separately. This formulation only penalizes the solution for errors that are greater than ϵ, a tolerance factor. For our experiments, we set ϵ to 0.01 and C to 50. It is possible to use the same method with a "kernel" that maps the input data into a higher feature space to permit nonlinear fits. The details are beyond the scope of this abstract, but we will present results for linear and Gaussian kernels. The latter is more expressive, and tends to provide a better regression fit, but is more expensive to compute.



(a) Atmospheric dust optical depth; the x-axis indicates L_s.



(b) Water ice cloud optical depth.

Figure 1: Optical depths predicted by two Gaussian SVMs trained on 1442 THEMIS daytime IR framelets (raw data), and evaluated on 72,061 framelets, from $L_s = 330°$ to $L_s = 161°$ (wrapped to $521°$). As in [3], values are clipped to the ranges shown.

Experimental Results: We constructed three regression models based on the training set (1442 framelets), then evaluated them on the full data set in terms of the square root of the mean squared error (RMSE) as well as the mean error (Merr):

	Dust		Ice	
Regression method	RMSE	Merr	RMSE	Merr
Linear least squares	0.043	0.031	0.037	0.022
Linear SVM	0.044	0.032	0.037	0.023
Gaussian SVM	0.037	0.025	0.036	0.017

While the linear SVM performs about the same as a linear least squares approximation, the Gaussian SVM is significantly better. In addition, we generally find slightly better accuracy in estimating water ice than in estimating dust. The mean accuracy obtained on both problems is within the 0.04 uncertainty of the τ values that we are trying to predict. The τ predictions of the Gaussian SVM for dust and for water ice are shown in Figure 1, as a function of time of year (L_s) and latitude. These results match those of Smith et al. quite closely, with the same dust event observed early on. However, the small dust event that takes place around $L_s = 155°$ (here, $515°$) is not visible. Likewise, the τ' values predicted for the water ice cloud optical depth are highly accurate, although they vary from τ in that they detect significant amounts of water ice north of $20°$ latitude from about $L_s = 470°$ to $500°$. We plan to further investigate these observations.

Conclusions: In this work, we have evaluated three regression models that analyze raw data collected by the THEMIS IR instrument and predict the optical depth for atmospheric dust and water ice clouds. Because this approach does not rely on calibration or any external sources of information about the atmosphere or surface conditions, it is well suited for use onboard THEMIS. Our experimental results show that SVM regression models can predict dust and water ice cloud optical depths with accuracy comparable to the uncertainty in the τ values being predicted. This approach could be used onboard THEMIS to permit passive monitoring for events of interest, such as early detection of dust storms and the identification of water ice clouds.

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