

Data Fusion of In-Flight Aerothermodynamic Heating Measurements Using Kalman Filtering

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On February 18th, 2021, the Mars 2020 entry system successfully delivered the Perseverance rover to the surface of Mars at Jezero Crater. The entry capsule carried a set of instrumentation installed on the heat shield and backshell, named the Mars 2020 Entry, Descent, and Landing Instrumentation. The instruments include pressure transducers, thermocouples, heat flux gauges, and radiometers to measure the aerodynamic and aerothermodynamic performance of the entry vehicle. Three of these sensors, a thermocouple plug, heat flux gauge, and a radiometer, are located in close proximity on the backshell. Each sensor is exposed to roughly the same environment, but measured these environments in different ways, each with its own set of modeling and measurement error complications. This paper develops a method for blending each of these measurements together in a single algorithm to produce estimates of the aerothermodynamic environments at that location on the backshell. The approach makes use of the Kalman filter methodology for solving state estimation problems. The filter has a predictor/corrector structure in which simplified process models are used to propagate the aeroheating states forward through time, which are then updated based on the measurement data. The method has been tested on simulated datasets.

Nomenclature

A_c, B_c, C_c	=	Convective heating correlation coefficients
A_r, B_r, C_r, D_r	=	Radiative heating correlation coefficients
c_1, c_2, c_3, c_4, c_5	=	Process and measurement model parameters
e	=	Surface emissivity
F	=	Derivative of f with respect to x
f	=	Process model
H	=	Derivative of h with respect to x
h	=	Measurement model
K	=	Kalman gain
k	=	Time index
P	=	Covariance of x
q_c	=	Convective heat flux, W/cm^2
q_r	=	Radiative heat flux, W/cm^2
R	=	Covariance of y

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T	= Temperature, K
t	= Time, s
u	= Filter process model inputs
V	= Freestream velocity, m/s
v	= Measurement noise
w	= Process noise
x	= Filter state
y	= Filter measurement
ρ	= Freestream atmospheric density, kg/m ³
σ	= Stefan-Boltzmann constant
$\hat{}$	= Filter estimate
$\bar{}$	= Filter prediction

I. Introduction

On February 18th, 2021, the Mars 2020 entry system [1] successfully delivered the Perserverance rover to the surface of Mars at Jezero Crater. The entry capsule carried a unique set of instrumentation installed on the heat shield and backshell, named the Mars 2020 Entry, Descent, and Landing Instrumentation (MEDLI2)[2, 3]. The instruments include pressure transducers, thermocouples, heat flux gauges, and radiometers to measure the aerodynamic and aerothermodynamic performance of the entry vehicle. The layout of the sensors is shown in Figure 1. The MEDLI2 sensor suite builds on the success of the Mars Science Laboratory Entry, Descent, and Landing Instrumentation (MEDLI), which flew on the heatshield of the Curiosity rover's entry capsule during its landing on Mars in August, 2012 [4–6]. The MEDLI2 sensor suite includes an enhanced set of instruments to make measurements in flight regimes and locations on the vehicle that were not captured in the MEDLI data.

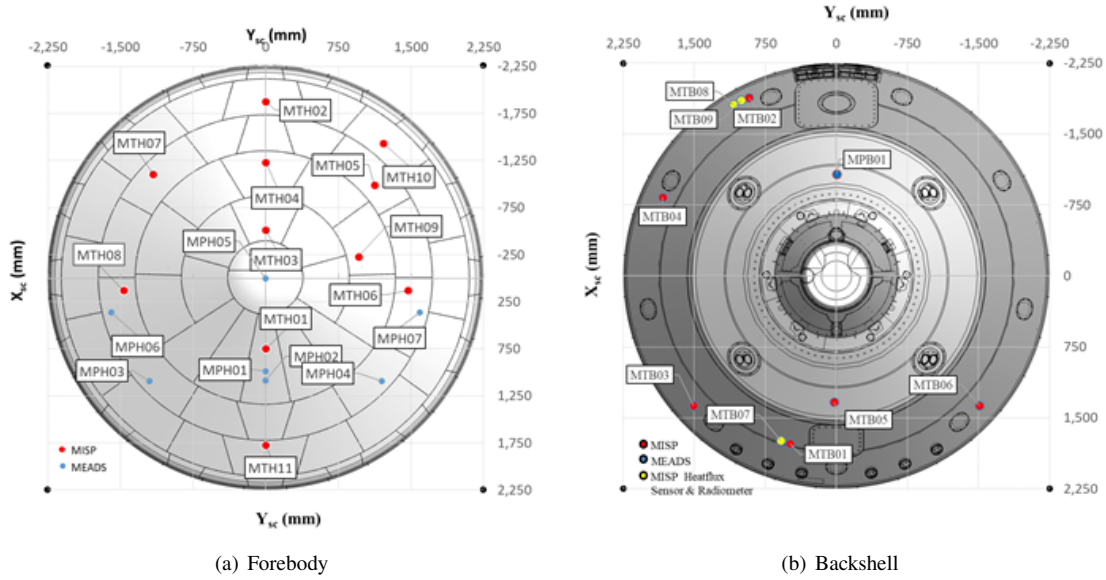


Fig. 1 MEDLI2 Sensor Layout

Note that three sensors on the backshell are located in close proximity: MTB02, MTB08, and MTB09. MTB02 is a thermocouple plug measuring temperatures at depths within the TPS. The heating environment can then be inferred through an ablator response model. MTB08 is a heatflux sensor, which measures the total convective and radiative heating directly, but the measurements are complicated by uncertain effects of catalycity and ablation products obscuring the measurement. The device is also set inside a copper housing, which acts as a heat sink, thus making the sensor output effectively a cold-wall heating measurement. MTB09 is a radiometer, which is essentially the same type of device as MTB08 but the heatflux measurement is made through a sapphire window such that the convective component

of heating is eliminated. This measurement is complicated by the uncertain effects of ablation products obscuring the window.

The purpose of this paper is to develop a unified framework for simultaneously processing data from each of these three sensors in order to produce estimates of the aeroheating environments at that location on the backshell during atmospheric entry. The approach makes use of a Kalman filter method for blending data from the three measurement sources. The Kalman filter incorporates models of each individual type of sensor and their associated systematic errors in order to produce an estimate of the aeroheating environment in a single, unified framework.

The remainder of this abstract is organized as follows. Section II describes the Kalman filter implementation for solving the aerothermal sensor fusion problem, including simplified process models and the sensor measurement models. Section III describes the results of applying the method to simulated data using a Monte Carlo technique to assess filter performance. Section IV describes future work that will be focused on applying the method to the flight data acquired during the Mars 2020 EDL.

II. Sensor Fusion Approach

A. Kalman Filter

The Kalman filter is a linear quadratic optimal estimation technique for blending multiple measurement sources and dynamic models of the process [13]. The filter has a predictor/corrector structure where estimates of the states are propagated forward in time and then corrections are obtained by processing external measurement data. The filter assumes process and measurement models for the system are of the form

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \mathbf{u}, \mathbf{w}, t) \quad (1)$$

$$\mathbf{y} = \mathbf{h}(\mathbf{x}, \mathbf{u}, \mathbf{v}, t) \quad (2)$$

The prediction step propagates the estimated states and covariance forward in time from measurement time t_{k-1} to time t_k according to the relations

$$\bar{\mathbf{x}}_k = \boldsymbol{\phi}(\hat{\mathbf{x}}_{k-1}, \mathbf{u}_{k-1}, \bar{\mathbf{w}}_{k-1}) \quad (3)$$

$$\bar{\mathbf{P}}_k = \boldsymbol{\Phi}_{k-1} \hat{\mathbf{P}}_{k-1} \boldsymbol{\Phi}_{k-1}^\top + \mathbf{B}_{k-1} \mathbf{Q}_{k-1} \mathbf{B}_{k-1}^\top \quad (4)$$

where ϕ represents numerical propagation of Eq. 1 from time t_{k-1} to t_k .

The measurement update takes the form

$$\hat{\mathbf{x}}_k = \bar{\mathbf{x}}_k + \mathbf{K}_k [\mathbf{y}_k - \mathbf{h}(\bar{\mathbf{x}}_k, \mathbf{u}_k, \bar{\mathbf{v}}_k, t)] \quad (5)$$

$$\hat{\mathbf{P}}_k = (\mathbf{I} - \mathbf{K}_k \mathbf{C}_k) \bar{\mathbf{P}}_k (\mathbf{I} - \mathbf{K}_k \mathbf{C}_k)^\top + \mathbf{K}_k \mathbf{D}_k \mathbf{R}_k \mathbf{D}_k^\top \mathbf{K}_k^\top \quad (6)$$

where $\mathbf{K}_k = \bar{\mathbf{P}}_k \mathbf{C}_k^\top (\mathbf{C}_k \bar{\mathbf{P}}_k \mathbf{C}_k^\top + \mathbf{D}_k \mathbf{R}_k \mathbf{D}_k^\top)^{-1}$.

B. Process Model

For application to the aerothermal sensor fusion problem, the states to be estimated include the convective and radiative heating components (q_c and q_r , respectively) and the temperature at the surface of the TPS, indicated by T . The Kalman filter requires a process model in order to propagate the states forward through the measurement data. Analytic approximate models can be utilized for this purpose. These relations take the form

$$q_c = A_c \rho^{B_c} V^{C_c} \quad (7)$$

$$q_r = A_r (\rho_{CO})^{B_r} (\rho_{CO_2})^{C_r} T^{D_r} \quad (8)$$

These relations are evaluated along the reconstructed entry trajectory [7]. Note that the radiative heating relation requires evaluation of shock parameters from CEA [14]. Once evaluated, the relations are simply pure functions of time, which can be differentiated numerically to provide the dynamics model describing the rate of change of the heating states along the trajectory.

The temperature state dynamics can be modeled using relations involving the temperature rate of change to the total heat rate and re-radiation. The model is of the form

$$\dot{T} = c_1 (q_c + q_r) + c_2 (T^4 - T_0^4) \quad (9)$$

where c_1 is a parameter relating to the transfer of heating into temperature change and $c_2 = -\sigma e$.

In summary, the process model takes the form $\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, t) + \mathbf{G}\mathbf{u}$ where

$$\mathbf{x} = \begin{Bmatrix} q_c & q_r & T \end{Bmatrix}^T \quad (10)$$

$$\mathbf{u} = \begin{Bmatrix} u_c & u_r \end{Bmatrix}^T \quad (11)$$

$$\mathbf{f} = \begin{Bmatrix} 0 \\ 0 \\ c_1 (q_c + q_r) + c_2 (T^4 - T_0^4) \end{Bmatrix} \quad (12)$$

$$\mathbf{G} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} \quad (13)$$

where u_c and u_r are the time derivatives of equations 7 and 8, respectively.

C. Measurement Models

The measurement data to be processed in the Kalman filter consists of the temperature and heat rate derived from the inverse analysis of the thermocouple sensors, the total heat rate measured by the heat flux gauge, and the radiative heat rate component measured by the radiometer. The measurement model takes the form $\mathbf{y} = \mathbf{C}\mathbf{x}$ where

$$\mathbf{C} = \begin{bmatrix} 0 & 0 & 1 \\ 1 & 1 & 0 \\ c_3 & c_4 & 0 \\ 0 & c_5 & 0 \end{bmatrix} \quad (14)$$

The parameters in the model include a correction factor for cold wall heat flux measurements (c_3), radiative absorption coefficient (c_4), and radiometer view factor compensation (c_5). Each of these parameters can be time varying and can also include corrections for ablation product deposition that would obscure the heat flux measurements.

III. Application to Simulated Data

In this section the Kalman filter approach is applied to a problem using synthetic data generated by numerical simulations using the process and measurement models to generate truth data, which is then corrupted by measurement noise of known statistics. Parameters of the simulation are shown in Table 1. The nominal states and measurements are shown in Figure 3. A 100 case Monte Carlo simulation was conducted in which perturbed states and measurements are processed by the Kalman Filter. The state errors are shown in Figure 4 along with the $\pm 3\sigma$ bounds that result from the estimate of the state covariance. The results indicate good filter performance for the given model.

Table 1 Model Parameters

Parameter	Value
c_1	5.0
c_2	-2.5515e-11
c_3	See Figure 2
c_4	0.94
c_5	See Figure 2

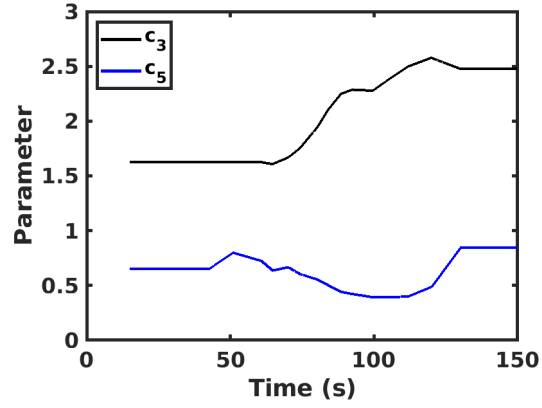


Fig. 2 Model Parameters c_3 and c_5

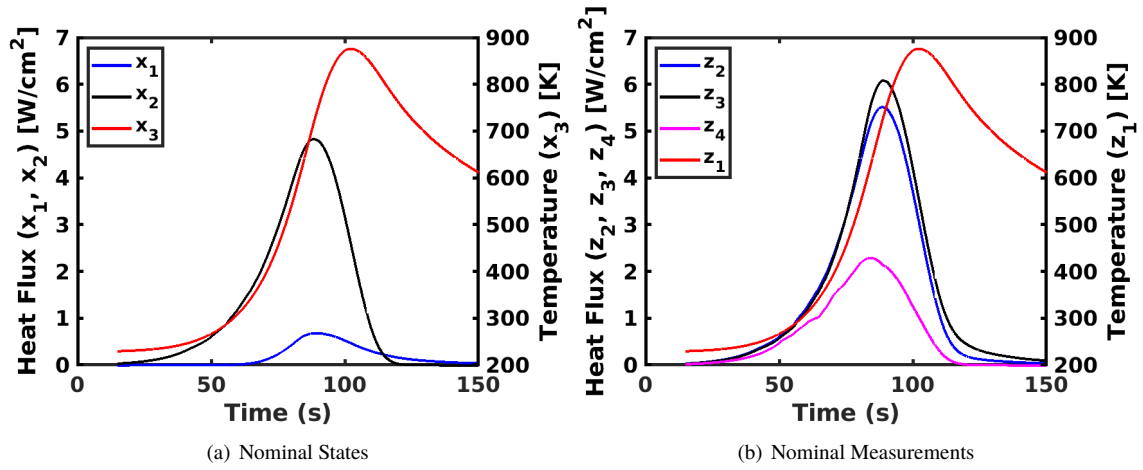
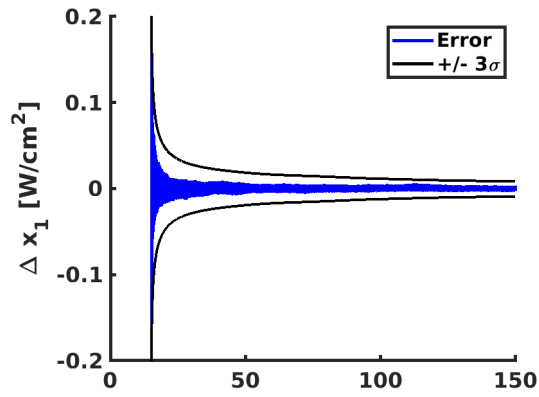
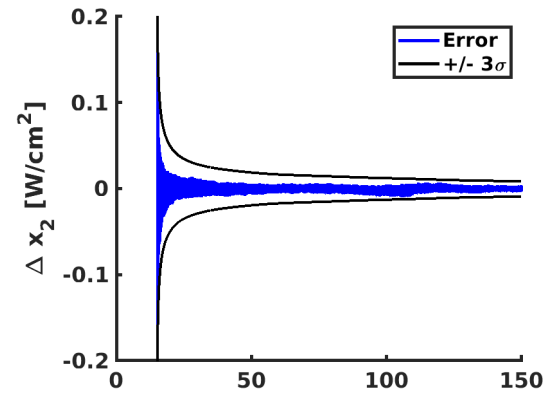


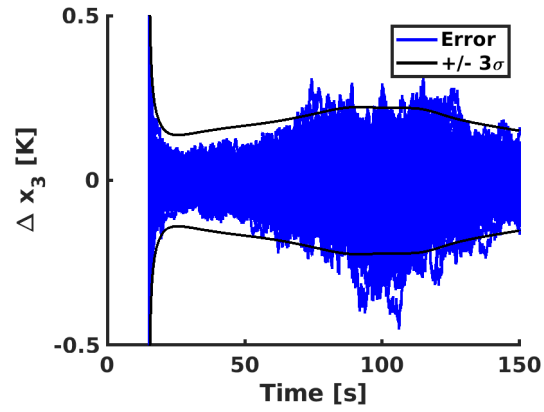
Fig. 3 Simulation States and Measurements



(a) Convective Heat Rate Error



(b) Radiative Heat Rate Error



(c) Temperature Error

Fig. 4 State Estimate Errors

IV. Application to the MEDLI2 Dataset

Future work will be focused on application of the Kalman filter framework to the MEDLI2 data set acquired during Mars 2020 EDL on February 18th, 2021. The flight measurements for the sensor fusion problem are shown in Figure 5.

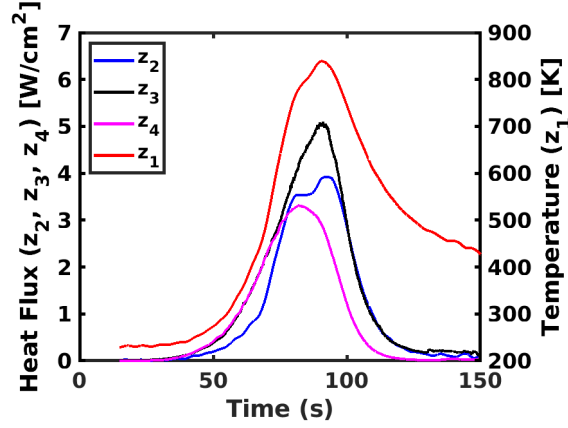


Fig. 5 MEDLI2 Flight Data

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