Hierarchical Navigation Algorithms

In Support of Mars Exploration

Robert H. Bishop
The University of Texas at Austin
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Topics for Today

- Navigation Algorithm Architecture Overview
- Event Detection during Interplanetary Cruise
- Application to Entry, Descent, and Landing

BACKGROUND

- Traditional navigation algorithms use batch least-squares estimation (OD) or extended Kalman filters.
  - LSE optimize over long data arcs and are not easily adapted to real-time operation.
  - EKFs often perform poorly outside the "tuned" region
- Environment changes are resolved by humans "in-the-loop" with an *ad hoc* and non real-time process relying heavily on:
  - Navigator Experience
  - Trial and Error Adaptation
- Our investigations led us to consider adaptive estimation.

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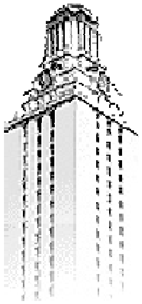
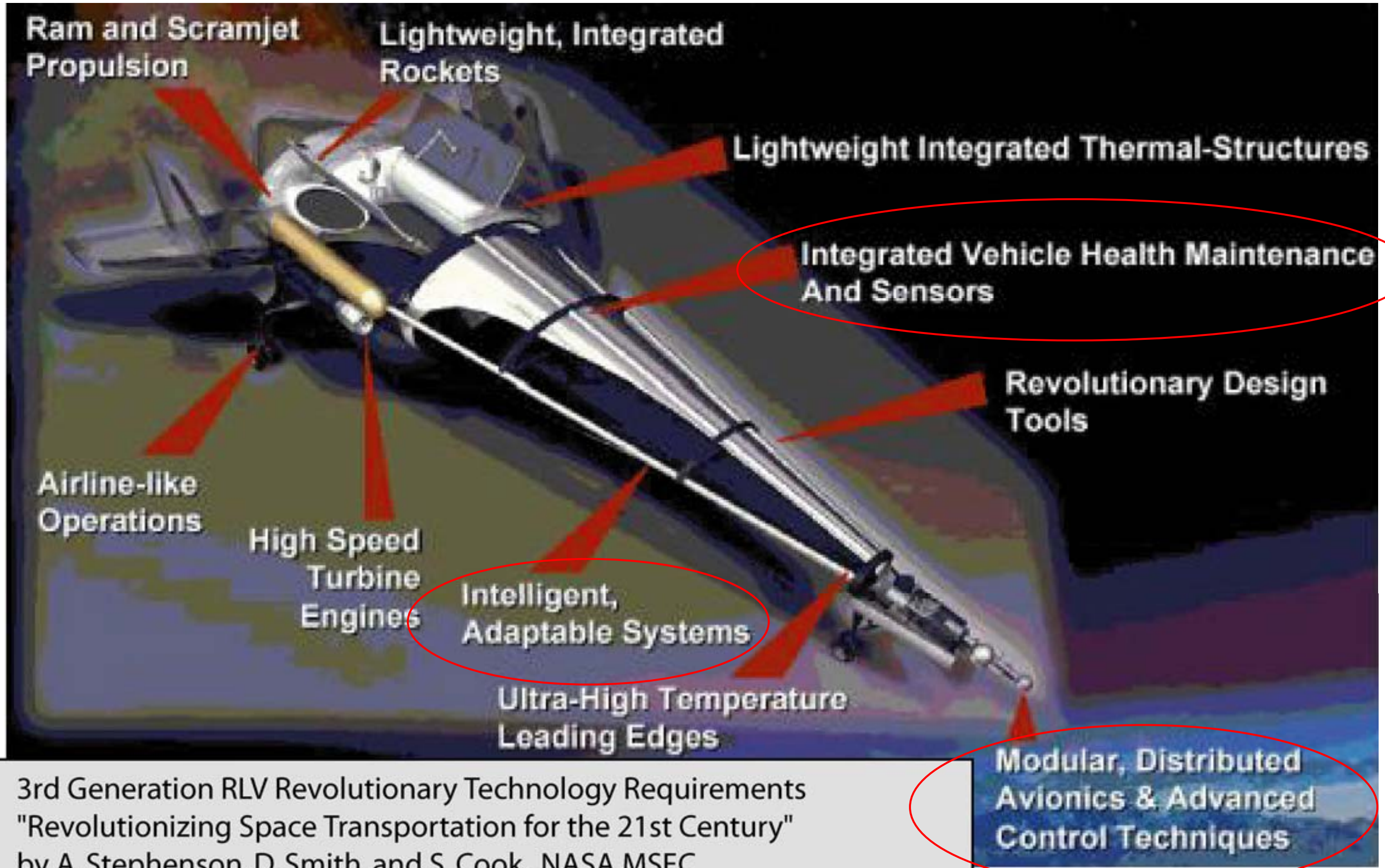
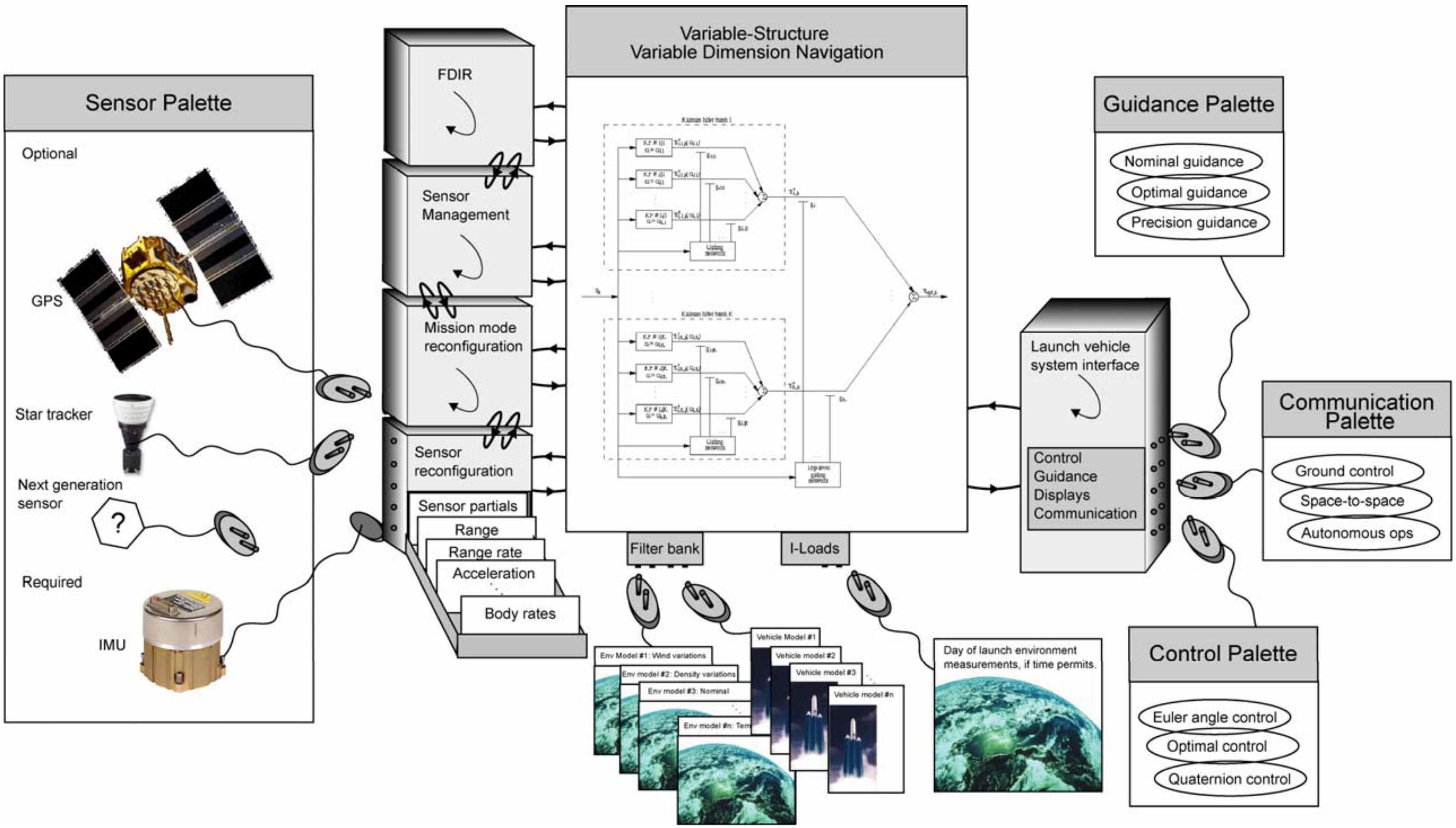


3RD GENERATION "DREAM VEHICLE"



3rd Generation RLV Revolutionary Technology Requirements
"Revolutionizing Space Transportation for the 21st Century"
by A. Stephenson, D. Smith, and S. Cook, NASA MSFC

PLUG-N-PLAY


Sensor Palette
Optional
GPS
Star tracker
Next generation sensor
?
Required
IMU
FDIR
Sensor Management
Mission mode reconfiguration
Sensor reconfiguration
Sensor partials
Range
Range rate
Acceleration
Body rates
Variable-Structure
Variable Dimension Navigation
Filter bank
I-Loads
Env Model #1: Wind variations
Env model #2: Density variations
Env model #3: Nominal
Vehicle Model #1
Vehicle model #2
Vehicle model #3
Vehicle model #n
Day of launch environment measurements, if time permits.
Launch vehicle system interface
Control
Guidance
Displays
Communication
Guidance Palette
Nominal guidance
Optimal guidance
Precision guidance
Communication Palette
Ground control
Space-to-space
Autonomous ops
Control Palette
Euler angle control
Optimal control
Quaternion control

WHY ADAPTIVE ESTIMATION?

- There is no systematic approach for selecting the operational navigation filter parameters.
  - Costly filter tuning in terms of manpower and time

- There is a need for greater state estimation accuracies with less data (of potentially lower quality).
  - Low-cost, high-performance

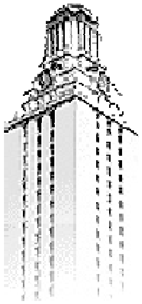
- There is a need to detect environmental and spacecraft changes and to take appropriate action.
  - Intelligent systems

- Desire to increase robustness and reliability.
  - Mission safety and success

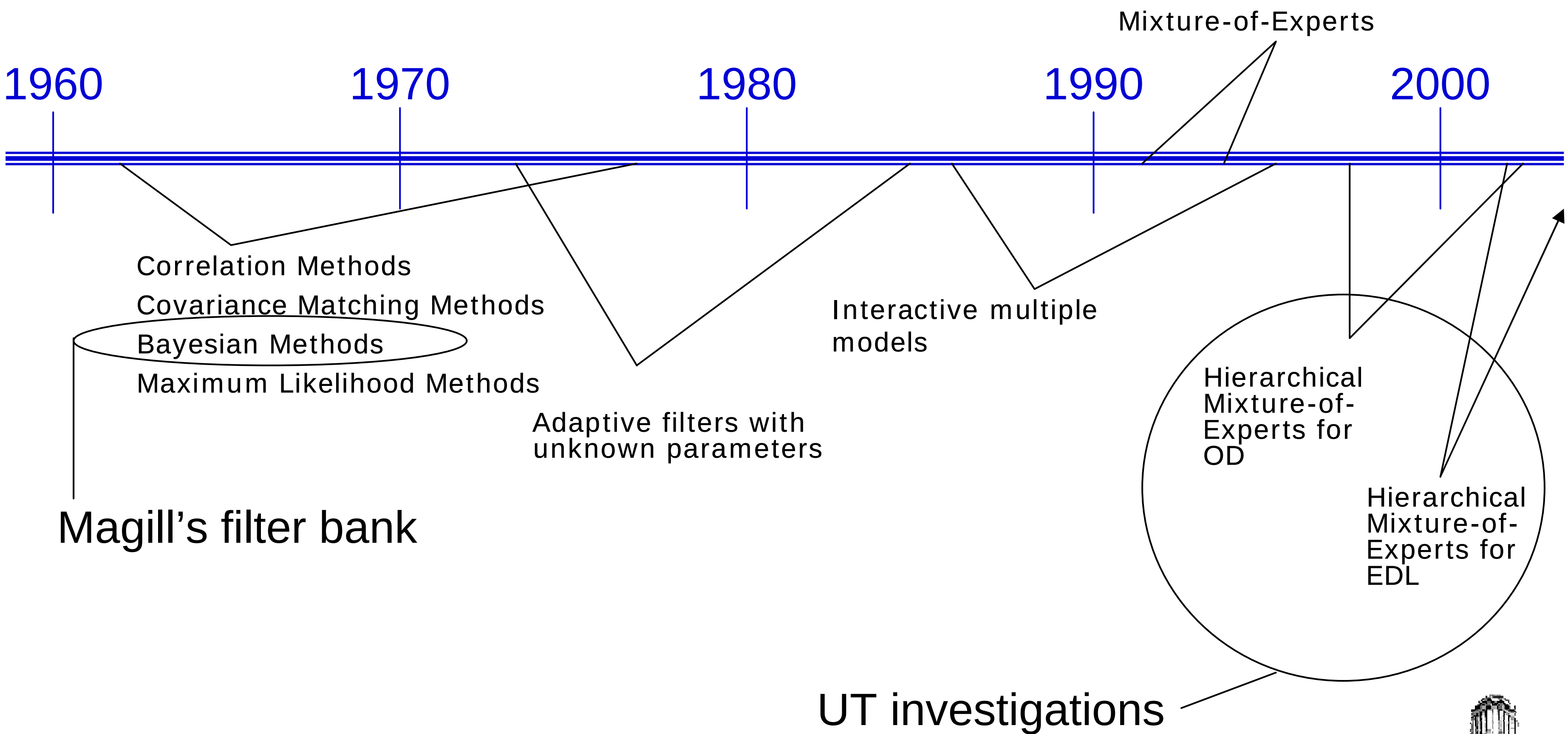
WHAT IS SUCCESSFUL ADAPTIVE ESTIMATION?

- Successful adaptive navigation algorithms:
  - Identify the nature of changes in the spacecraft environment that cause it to deviate from the expected.
  - Tune the filter and model parameters corresponding to these changes to resume optimal tracking.

- The adaptive algorithm must perform these tasks with a general structure based upon numerical analysis of the available data.



EVOLUTIONARY PROCESS



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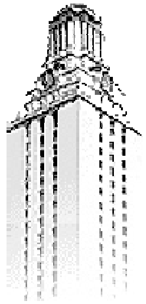
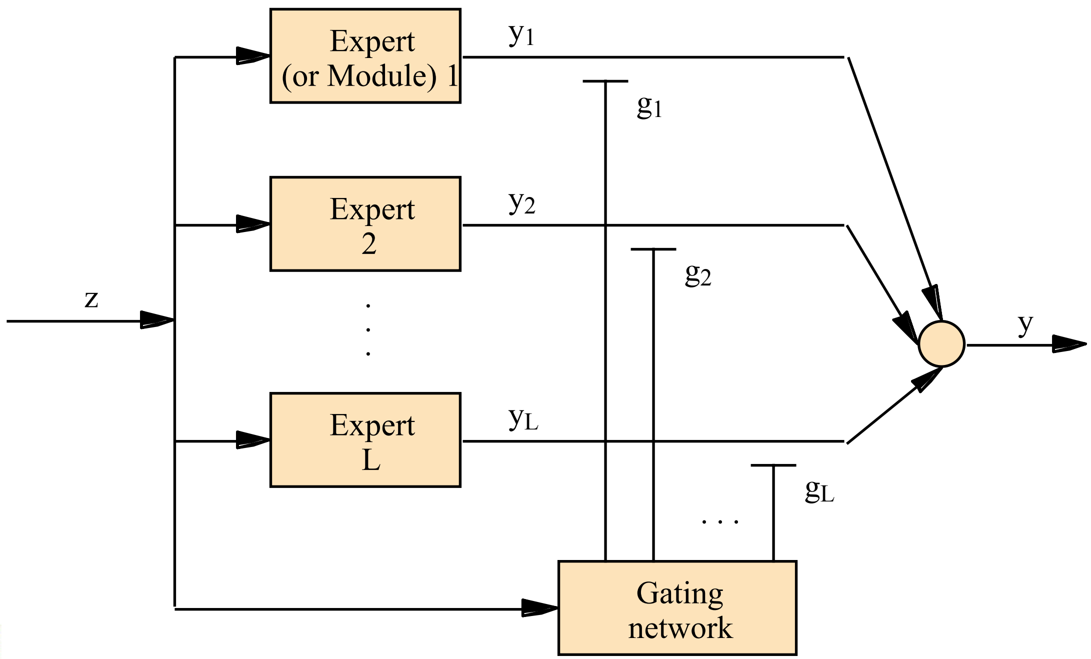


HIERARCHICAL MIXTURE-OF-EXPERTS

- Each module is an expert network— a Kalman filter.
- The function z is the input vector—the measurements.
- The function y_i is the ith module output—state estimate and error covariance.
- The function g_i is the activation of the ith output neuron of the gating network.



GATING NETWORKS

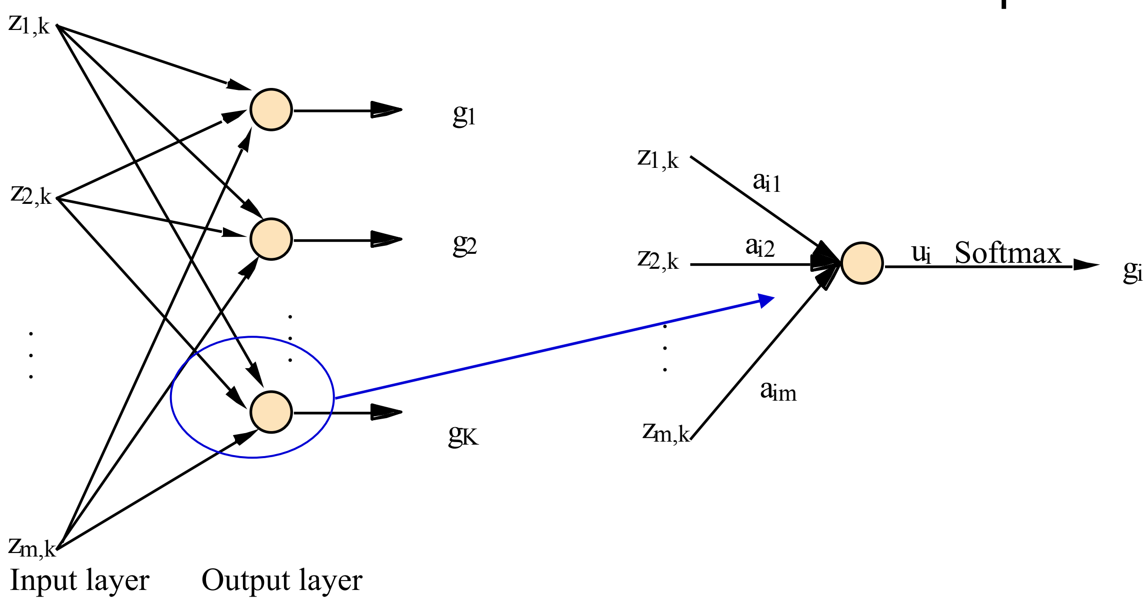
- The i^{th} filter is associated with a GN neuron with synaptic weight $a_{i,k}$
- The GN calculates gating weights, g_i, by mapping synaptic weights via the *softmax* operation
- Why softmax?
  - Differentiable function that preserves rank order
  - Generalization of a "winner-takes-all" operation

$$u_i = z_k^T \mathbf{a}_i$$

$$g_i = \frac{e^{u_i}}{\sum_{i=1}^{L} e^{u_i}}$$

$$0 \le g_i \le 1, \quad \forall\ i=1, 2, \ldots L$$

$$\sum_{i=1}^{L} g_i = 1$$



SYNAPTIC WEIGHT UPDATE FORMULA

- Conditional density function

$$f(\mathbf{z}_k|\alpha_i) = \frac{1}{\sqrt{2\Pi|\mathbf{W}_k|}} e^{-\frac{1}{2}\mathbf{r}_k^T \mathbf{W}_k^{-1} \mathbf{r}_k}$$

- Distribution of the bank
  - The g's may be interpreted as *apriori* probabilities

$$f(\mathbf{z}_k) = \sum_{i=1}^{L} f(\mathbf{z}_k|\alpha_i) g_i$$

- Learning is achieved by maximizing log-likelihood l with respect to $\boldsymbol{g(a)}$

$$l = \ln f(\mathbf{z}_k) = \ln \sum_{i=1}^{L} g_i f(\mathbf{z}_k|\alpha_i)$$

- Instantaneous *a posteriori* probability injects filter performance into learning

$$h_i = \frac{f(\mathbf{z}_k|\alpha_i) g_i}{\sum_{i=1}^{L} f(\mathbf{z}_k|\alpha_i) g_i}$$

- Synaptic weights update

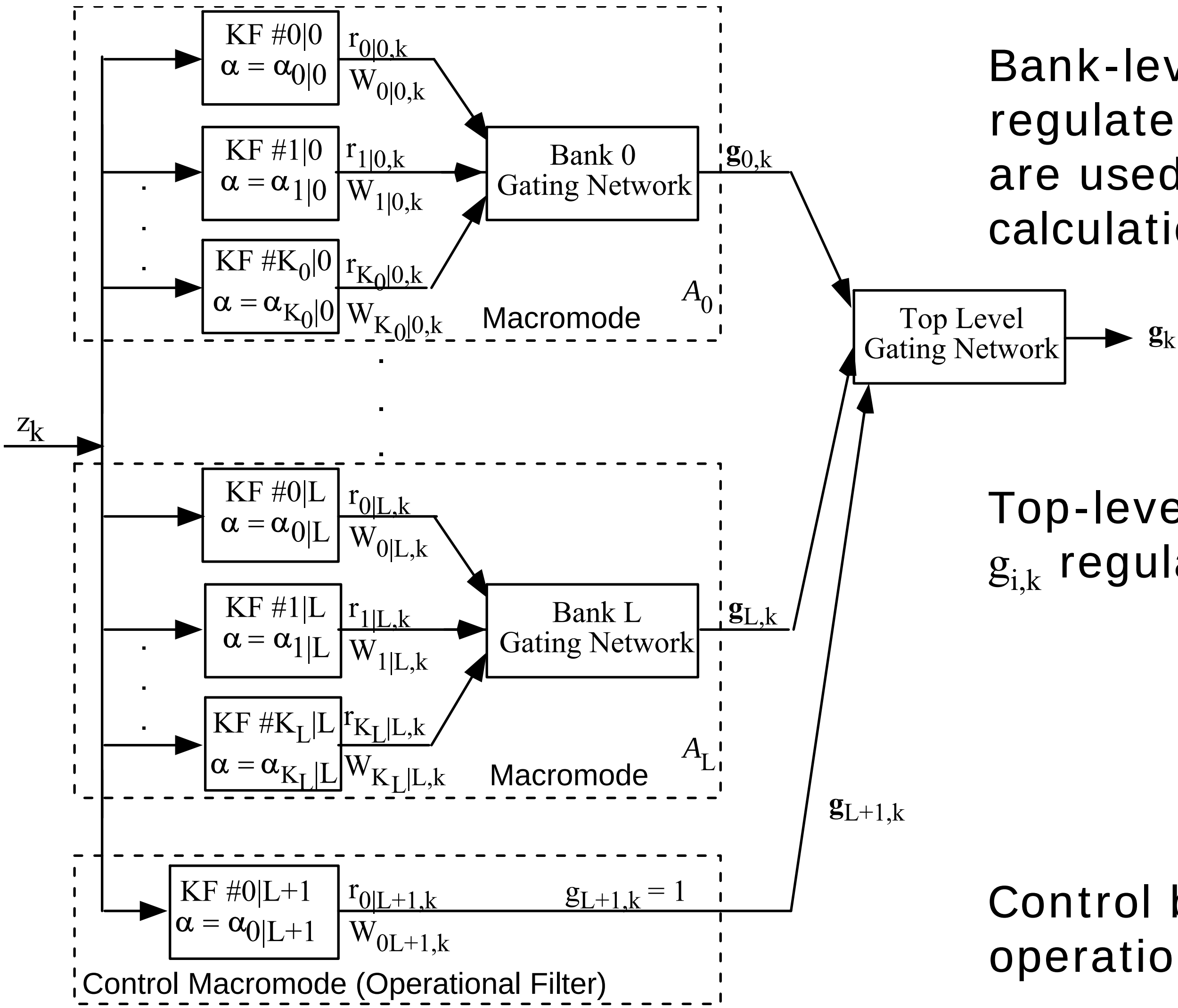
$$a_i \rightarrow a_i + \eta(h_i - g_i)\mathbf{z}_k$$

Learning rate

MULTIPLE LEVELS OF MODULARITY

- Filters are collected into banks to represent <u>macromode</u> environment changes
- Within each bank, individual filter realizations represent fine, <u>micromode</u>, environment changes
- "Best" filter in HME has the highest bank-level $g_{ji,k}$ in the bank with the highest top-level $g_{i,k}$
- Optimal filter configuration can be "masked" when containing bank does not receive highest top-level g
- Method desired for identifying nominal environment without bank "masking": Operational Control bank
  - The operational filter parameters and model reflect the mission nominal environment
  - The top-level GN identifies the nominal environment by selecting the control bank

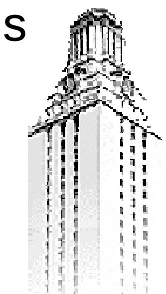
MULTIPLE-LEVEL HME ARCHITECTURE



Bank-level weights $g_{ji,k}$ regulate micromodes and are used in top-level calculation.

Top-level weights $g_{i,k}$ regulate macromodes

Control bank only contains operational filter

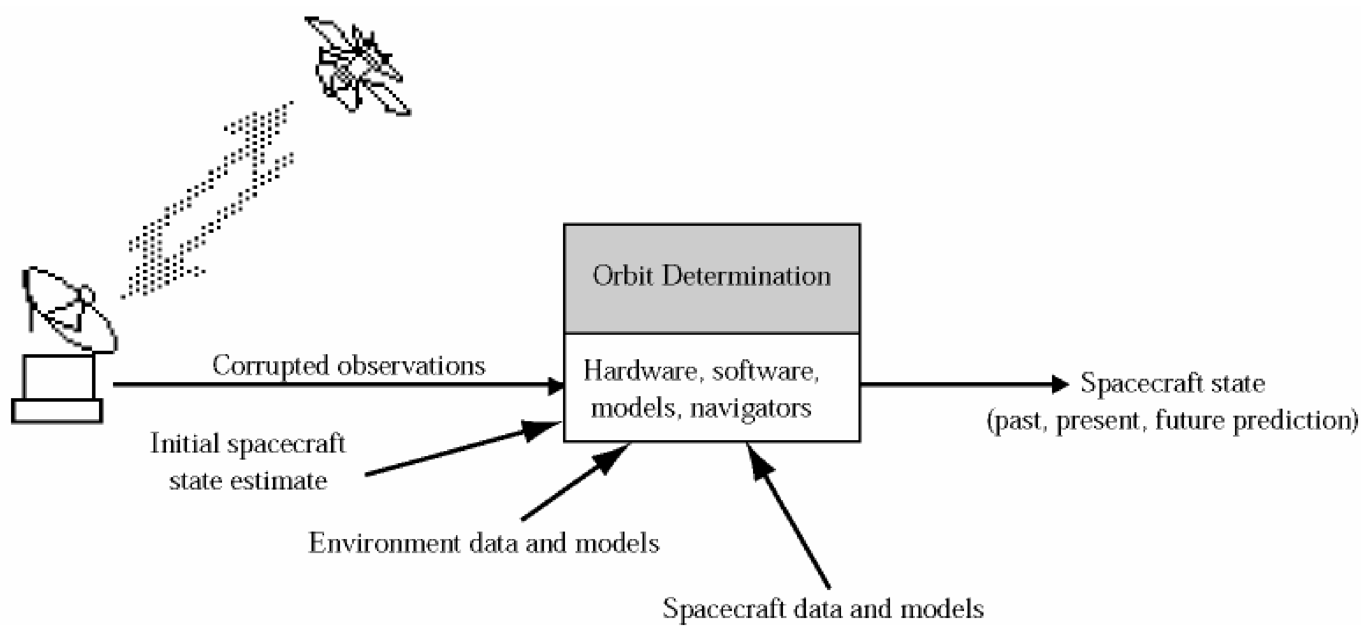


APPLICATIONS

- Interplanetary cruise orbit determination
  – Detecting small discrete disturbances
  – Detecting slow continuous disturbances
- Mars atmospheric entry
  – Processing IMU as a “measurement”
  – Detecting atmospheric density variations

WHAT IS ORBIT DETERMINATION?

- **Orbit Determination (OD):** The process of describing the past, present, or predicted position of a satellite in terms of the orbital parameters.



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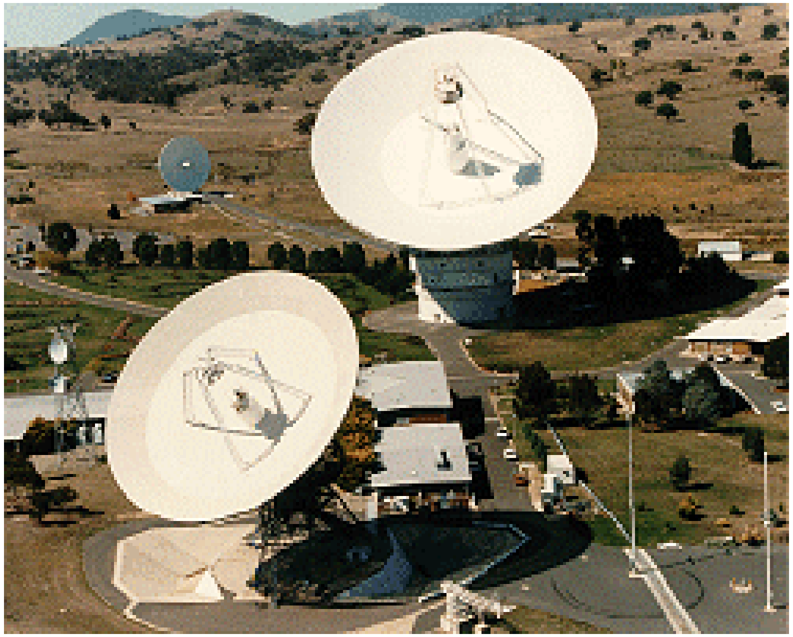
THE DEEP SPACE NETWORK

- Interplanetary tracking is accomplished by 34 and 70m dishes
- DSN dish time is expensive and in high demand
- The primary data type is Doppler with a large number of supporting range measurements



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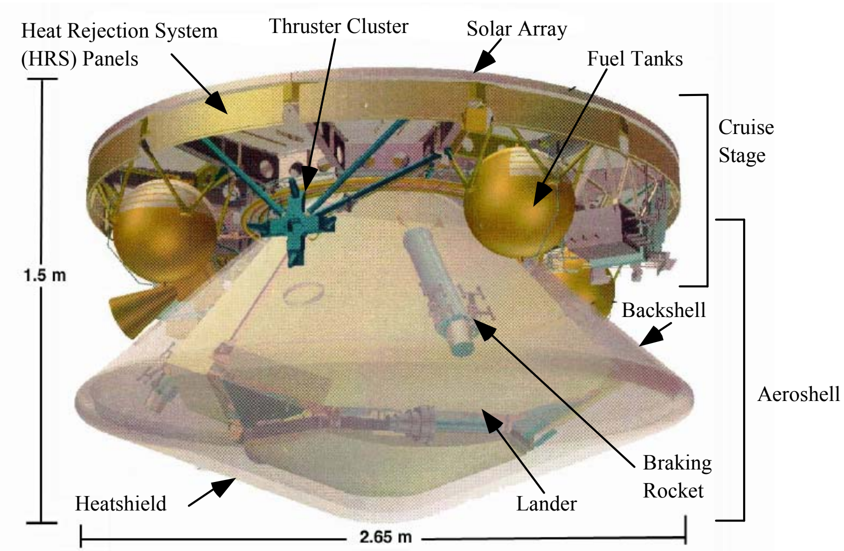
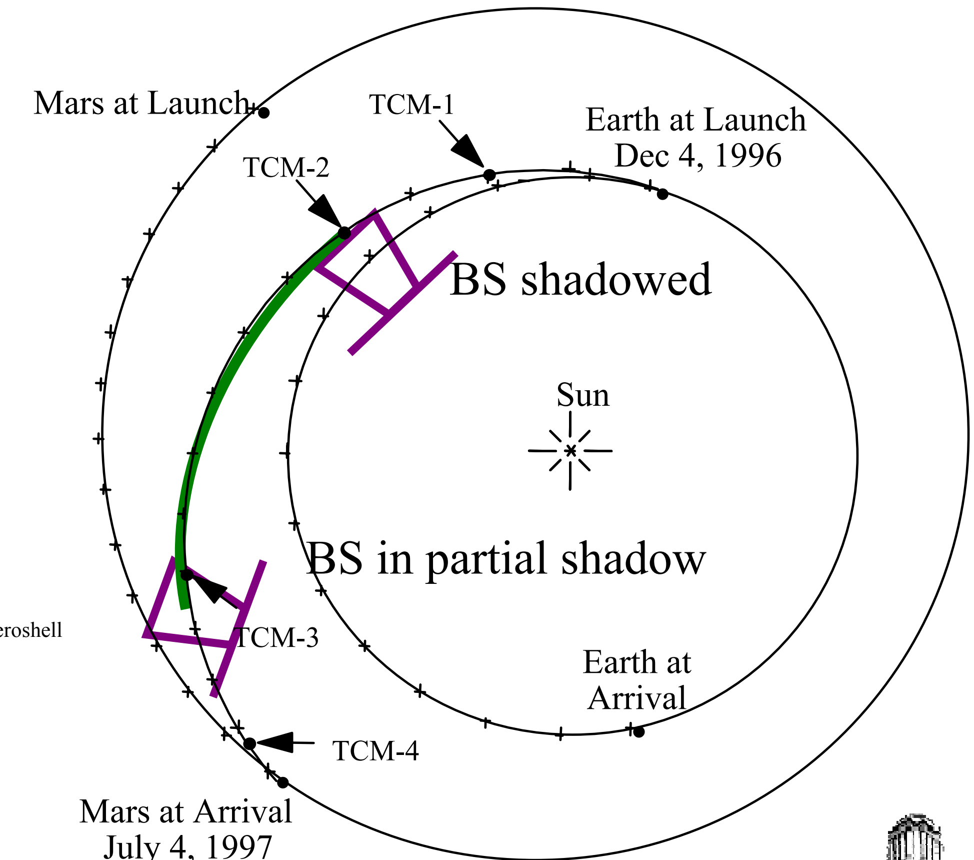
SOLAR RADIATION PRESSURE MODELING & SMALL FORCE DETECTION



MARS PATHFINDER (MPF)



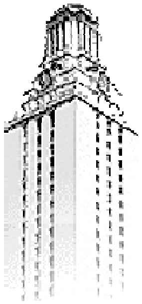
15-Day Time Tics

TCM=Trajectory Correction Maneuver

SRP MODEL SELECTION

- The process of tuning the operational filter during the Mars Pathfinder mission was very time-consuming for the navigation team.
- One of the main difficulties was choosing solar flux parameters.
- We considered this situation using the mixture-of-experts architecture.

MPF navigation team best SRP model		
Spacecraft Part	**Component Type**	**Active**
Solar array	Flat plate	Entire cruise
Launch vehicle Adapter	Flat plate	Entire cruise
Heat rejection system	Cylinder	Entire cruise
Backshell 1	Cylinder	Before 4/16/97
Backshell 2	Flat plate	After 4/16/97

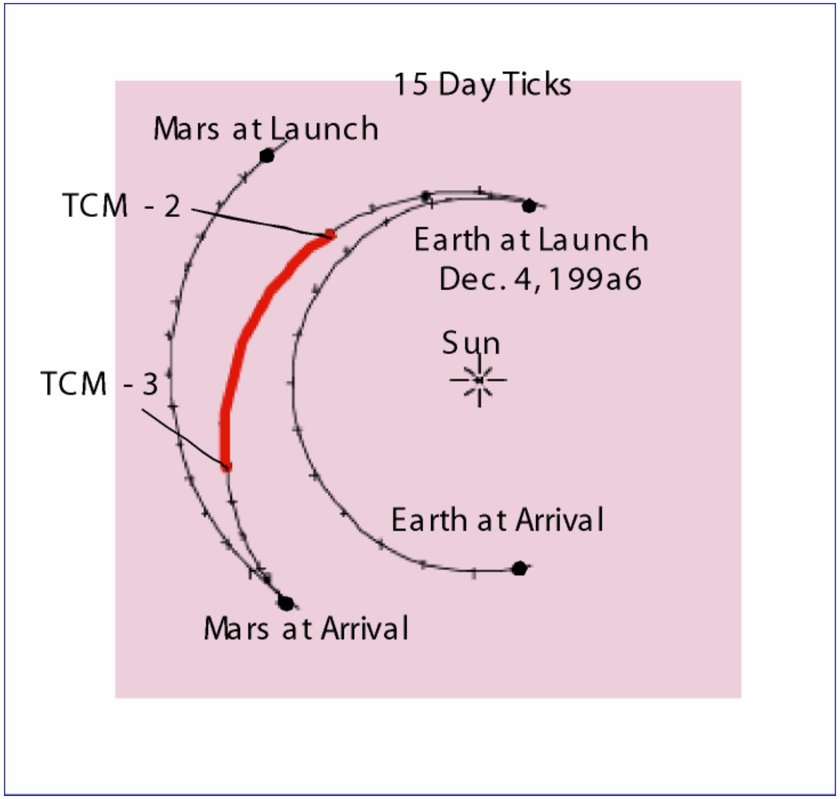


GENERAL HME CONFIGURATION: 5 BANKS

- **Bank 0**: Impulsive Velocity Macromode
  - Filter and model parameters
- **Bank 1**: SRP Environment Macromode
  - Filter and model parameters
- **Bank 2**: Doppler Noise Macromode
  - Filter parameters
- **Bank 3**: Range Noise Macromode
  - Filter parameters
- **Bank 4**: Experimental Control (Nominal Operation)

PROCESSING DSN DATA FROM MPF MISSION

- MPF Cruise from TCM-2 to TCM-3
  - Feb. 4 to Apr. 18, 1997
  - 1612 Doppler and 3144 range observations
- Unmodeled Impulsive Maneuver Identification
  - March 25 maneuver omitted from filter models
- SRP Environment Change Identification
  - MPF model 4 assumed operational model



IMPULSIVE MANEUVER IDENTIFICATION

- The following small correction (0.7 mm/sec) was performed on March 25, 1997
    - $\Delta V = [0.4449\ 0.07304\ 0.5301]$ mm/sec

- The modeled Doppler noise = 0.2 mm/sec

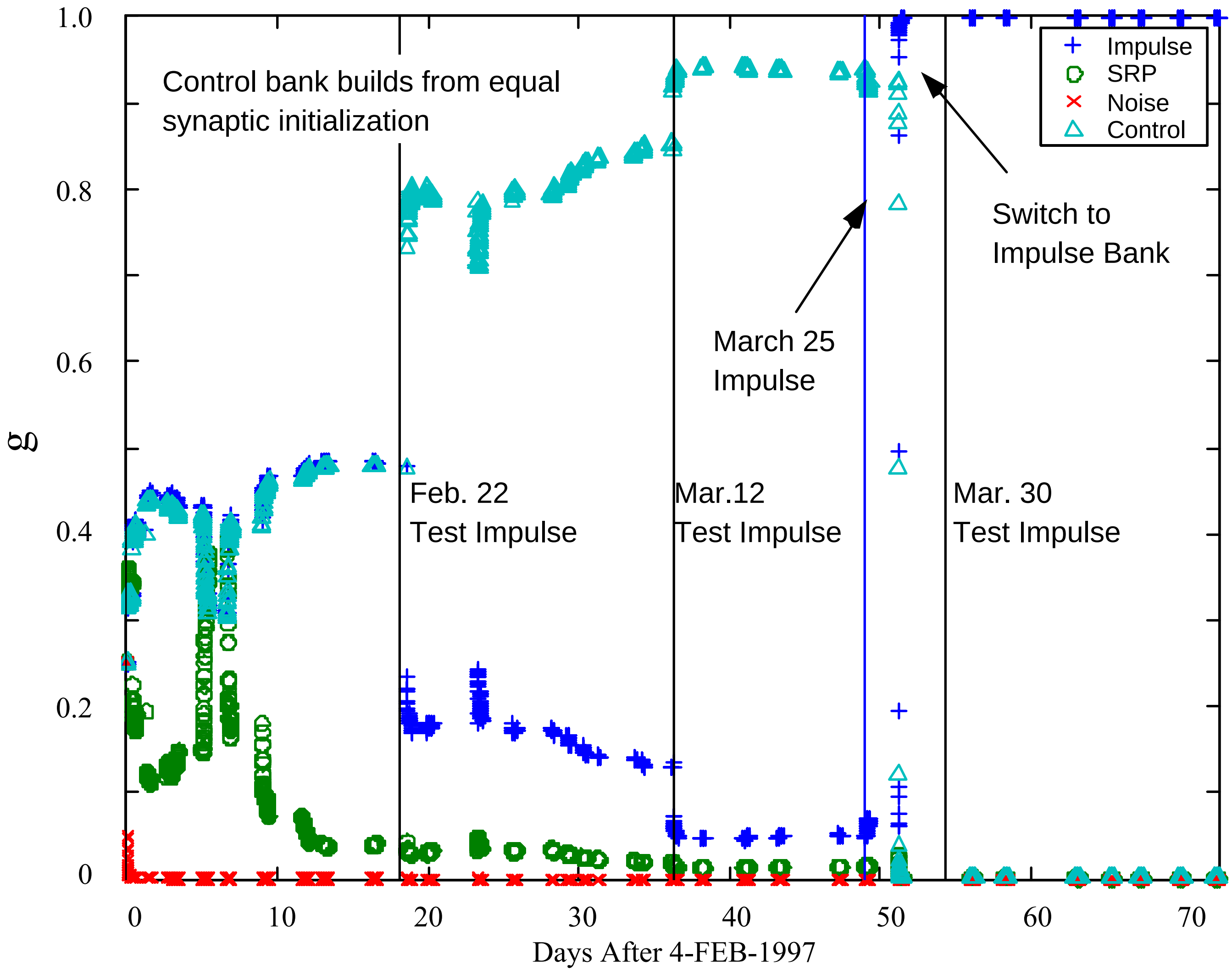
- This maneuver has been omitted from all filter dynamic models to simulate an unmodeled impulsive event in the real mission data.

- Successful experiment will result in Control receiving highest top-level weight until March 25 when a switch to the Impulse macromode occurs.

IMPULSE HME CONFIGURATION

	Bank #	Filter #	Impulse	SRP	R
Impulse	0	(0,0)	Feb. 4	*	*
	0	(1,0)	Feb. 22	*	*
	0	(2,0)	Mar. 12	*	*
	0	(3,0)	Mar. 30	*	*
SRP	1	(0,1)	---	MPF 2	*
	1	(1,1)	---	MPF 4	*
Noise	2	(0,2)	---	*	X3
	2	(1,2)	---	*	X9
Control	3	(0,3)	---	*	*

IMPULSE IDENTIFICATION TOP-LEVEL



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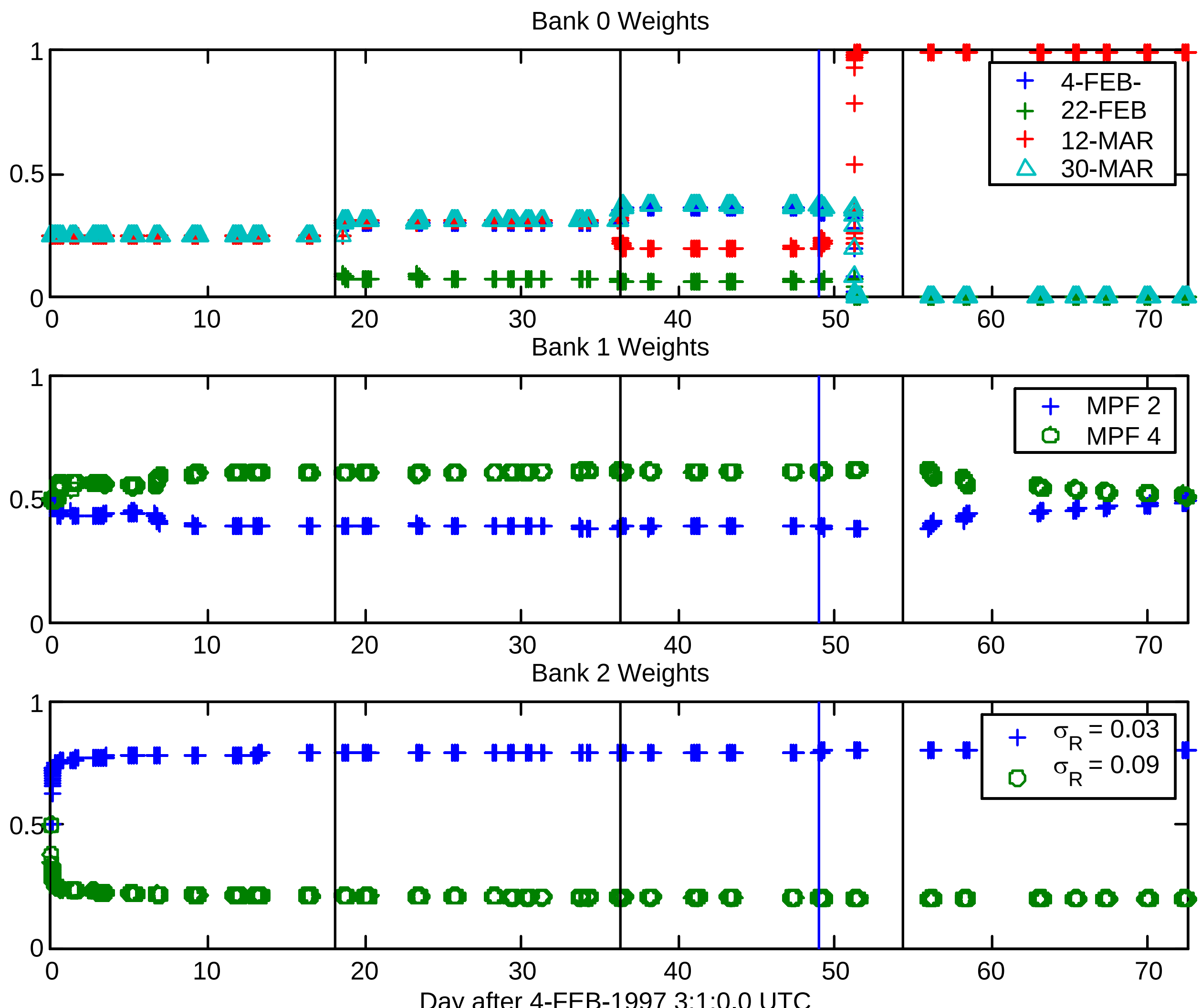
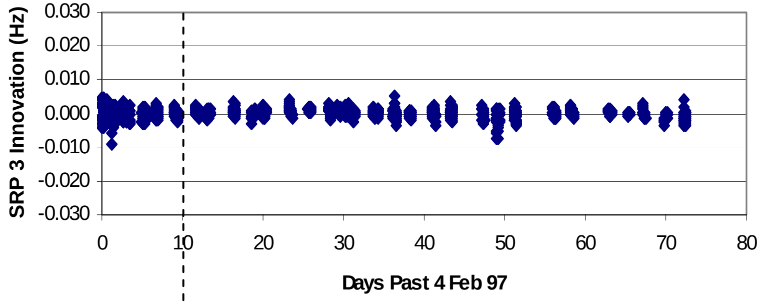
IMPULSE IDENTIFICATION BANK-LEVEL

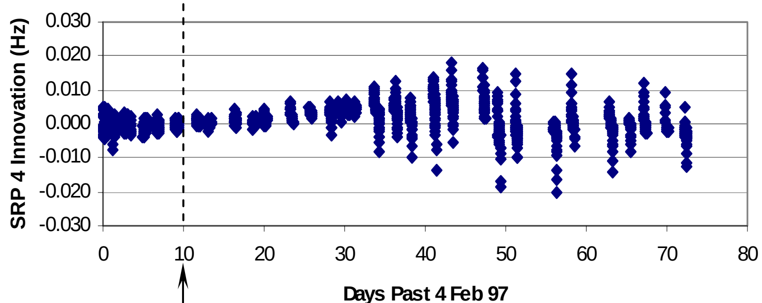


CHANGES IN SRP ENVIRONMENT

- Changes in SRP environment represent continuous and low-level changes in spacecraft dynamics
- Although not necessarily critical, it is important to identify SRP as a source of OD error.
- MPF model 4 is assumed to be operational model and the GA optimized model is included in the SRP identification macromode.
- The March 25 maneuver is omitted from all models to examine ability to distinguish between discrete and continuous model changes.

OPTIMAL SRP MODEL



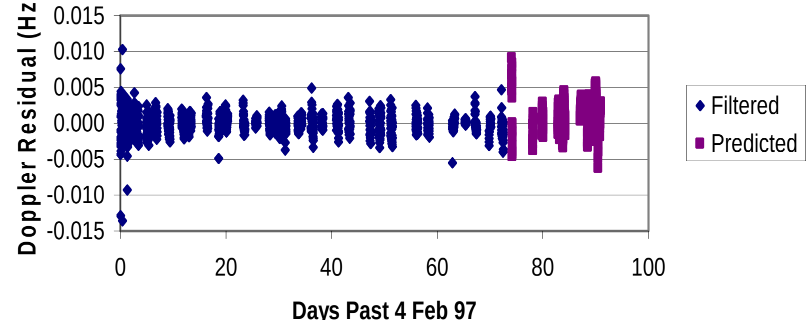


The GN determines that the SRP3 model is better than SRP4 with only 10 days of Doppler residual data.

Preliminary Best from GA w/ Single Point Crossover

(f = .29 after 20 iterations)

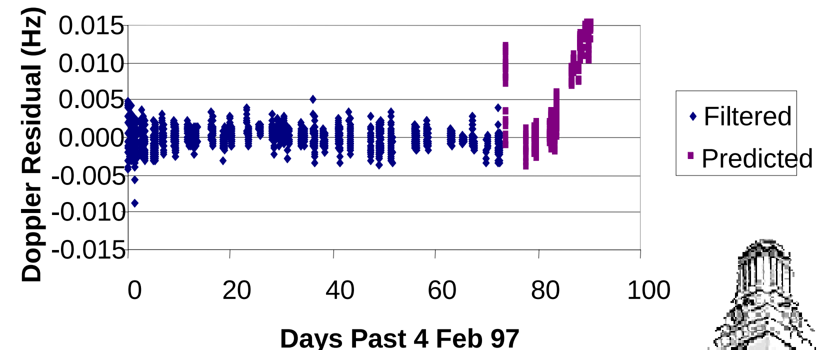
Note: There are a few transients/outliers not seen at this scale

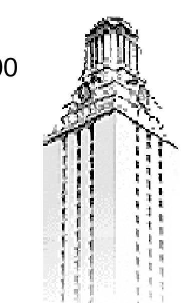


MPF Team Best Result (SRP Model 3)

(f = .32)

Note: There are a few transients/outliers not seen at this scale





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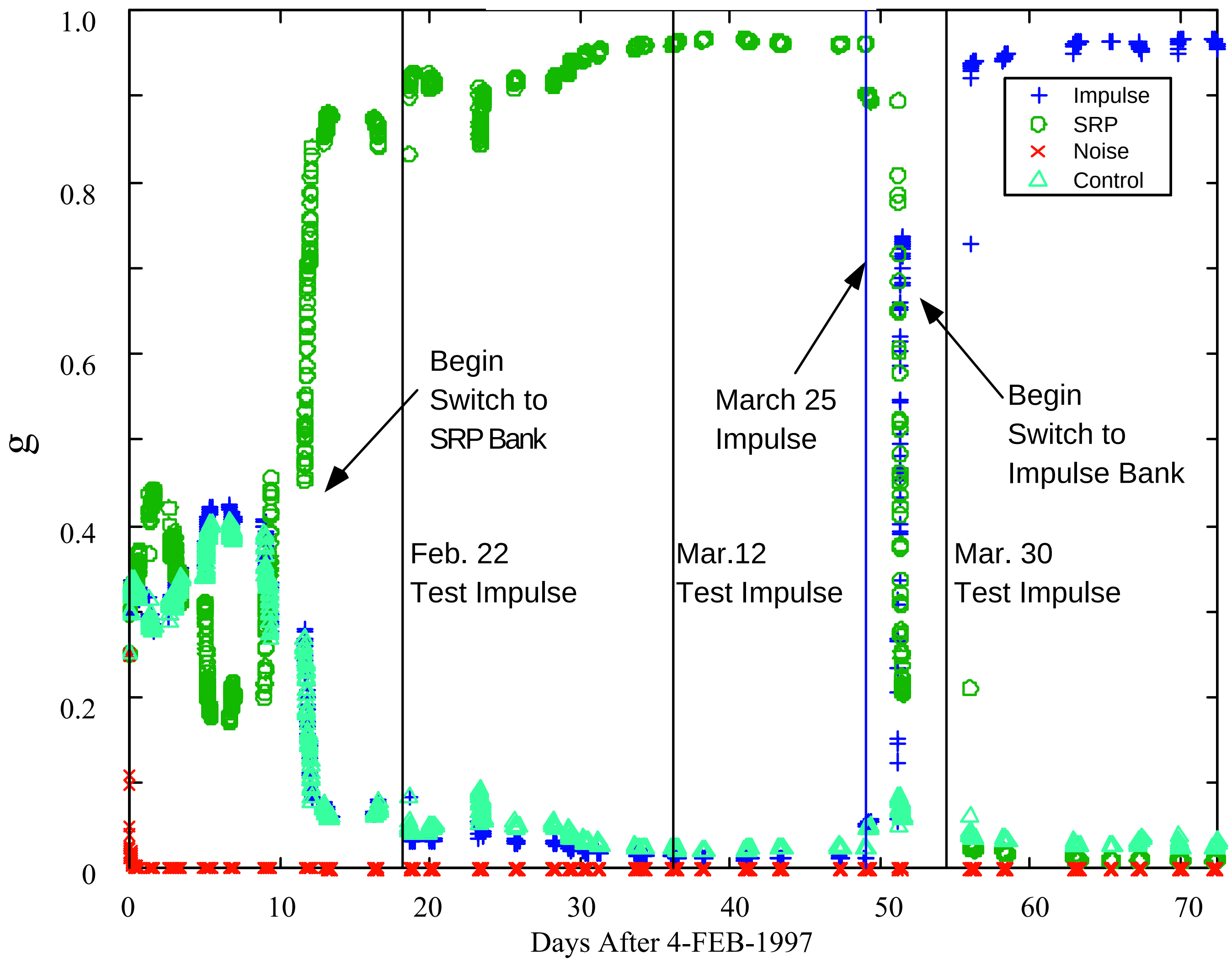
SRP HME CONFIGURATION

	Bank #	Filter #	Impulse	SRP	R
Impulse	0	(0,0)	Feb. 4	MPF 4	*
	0	(1,0)	Feb. 22	MPF 4	*
	0	(2,0)	Mar. 12	MPF 4	*
	0	(3,0)	Mar. 30	MPF 4	*
SRP	1	(0,1)	---	MPF 2	*
	1	(1,1)	---	Ely	*
Noise	2	(0,2)	---	MPF 4	X3
	2	(1,2)	---	MPF 4	X9
Control	3	(0,3)	---	MPF 4	*

SRP IDENTIFICATION TOP-LEVEL



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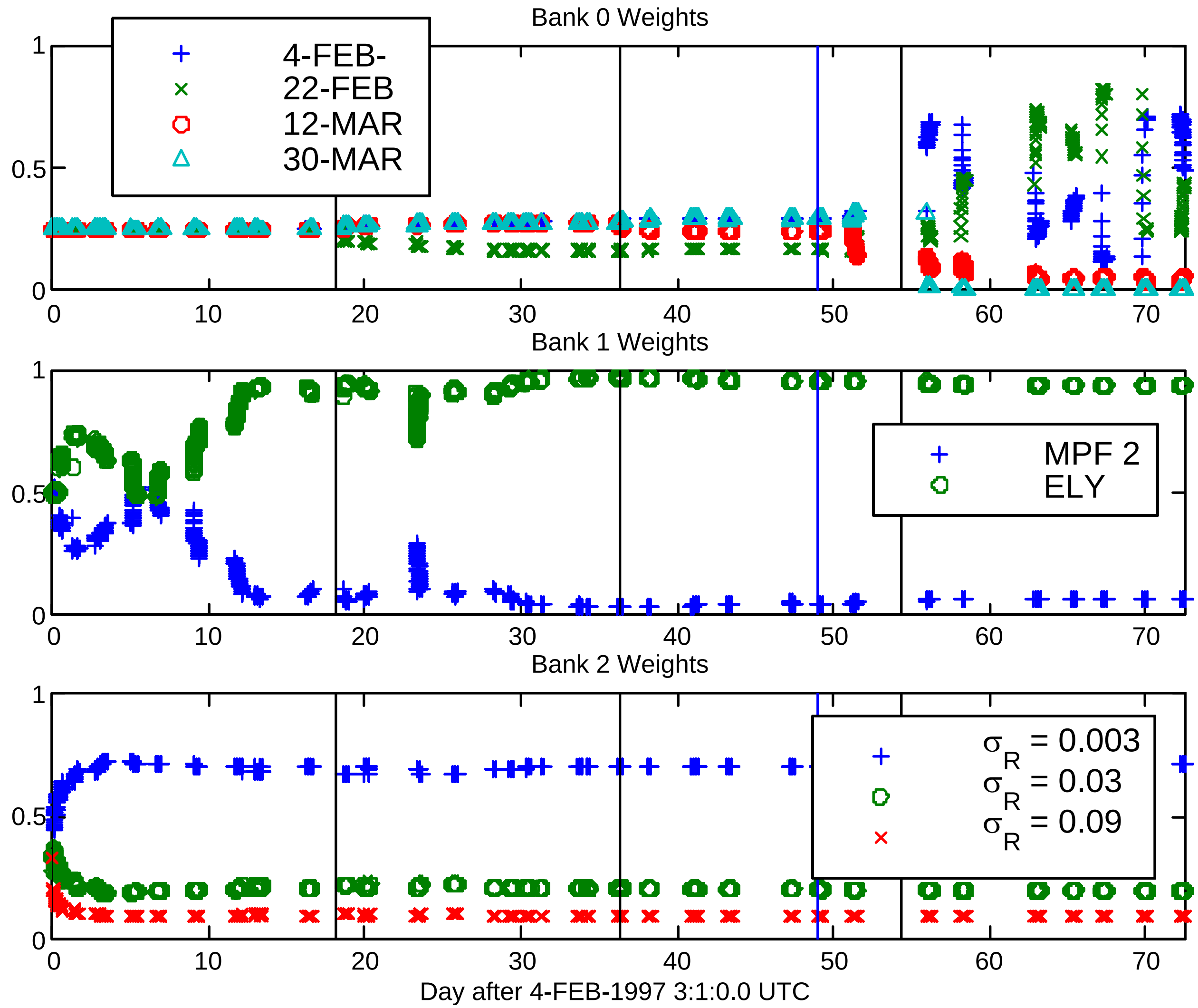
SRP IDENTIFICATION BANK-LEVEL



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SUMMARY: HME OD PERFORMANCE

- The top-level GN correctly identified the first macromode change in all cases.
  - False detections avoided at test impulse times.
  - Decisions based upon residual signatures near level of measurement noise.
  - Distinguished continual and discrete dynamic changes.

- Bank-level GN identified appropriate micromodes in most cases, but work remains in placement of test impulse times.

- Concept proven in simulation with actual DSN interplanetary cruise tracking data.

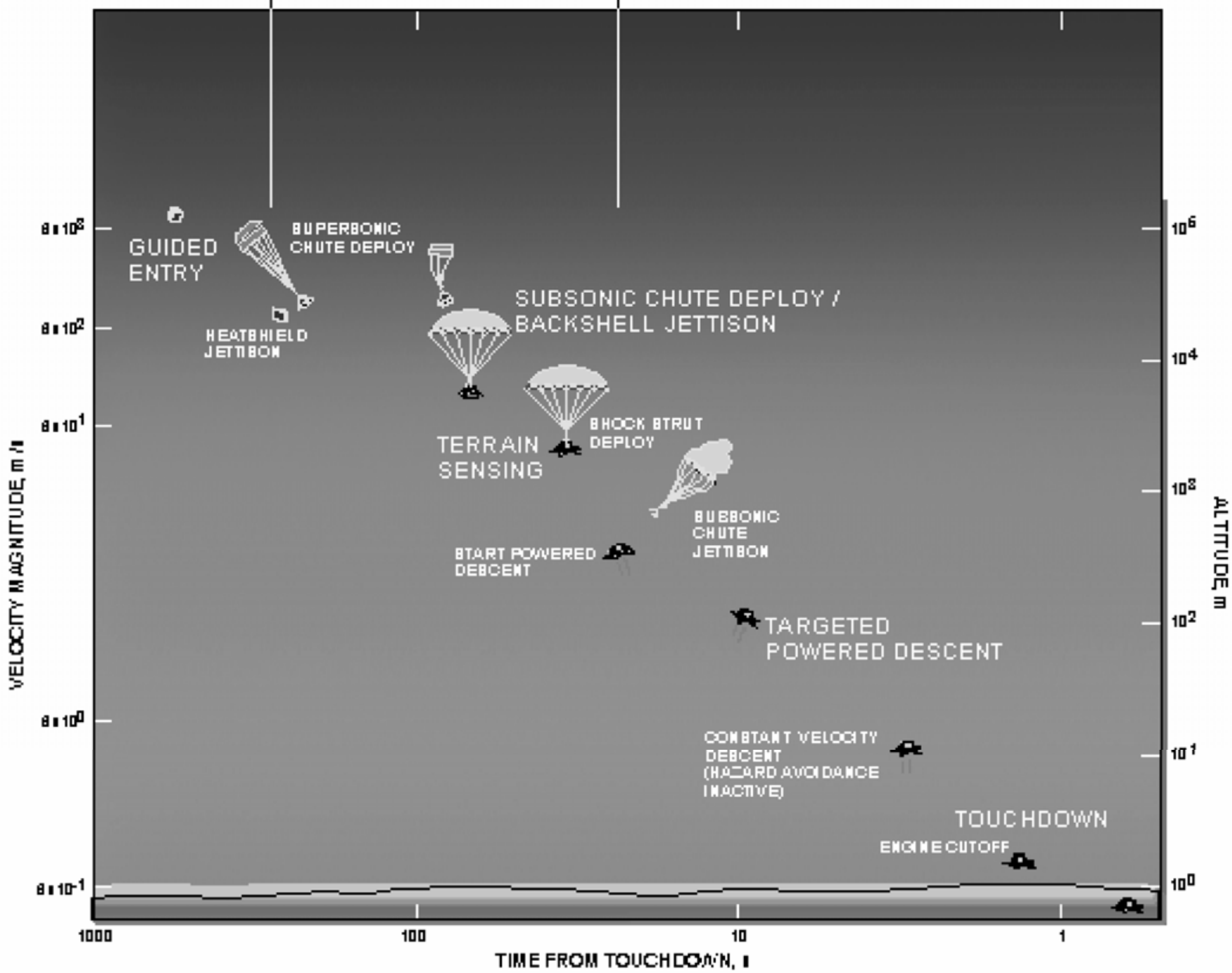
APPLICATION TO MARS ENTRY

- **Objective**: Develop entry navigation flight software to support actively guided Mars entry.
- To date no Mars lander has employed active guidance with real time, onboard state estimation.
- Uncertainty in landing can be measured in hundreds of Kms.
- Future missions will require ability to land within a few Kms or less of the intended point—precision landing.
- The part of the entry before parachute deployment is the most challenging, as being dynamically intensive but poor in measurements.

Active guidance with IMU dead-reckoning navigation

No guidance with IMU-aided recursive navigation and terrain sensing

Active terminal phase guidance with hazard detection and avoidance and IMU-aided recursive navigation



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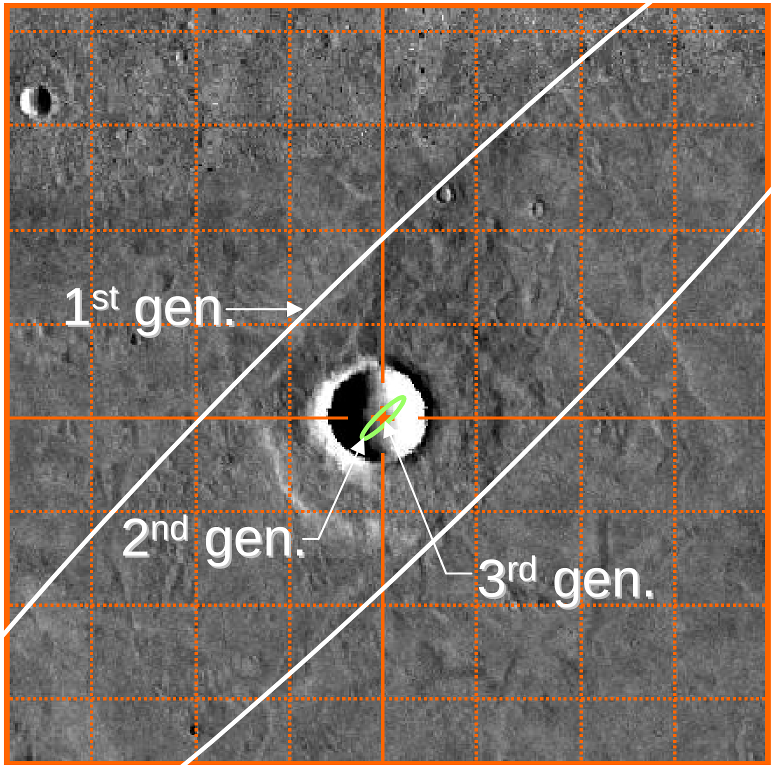
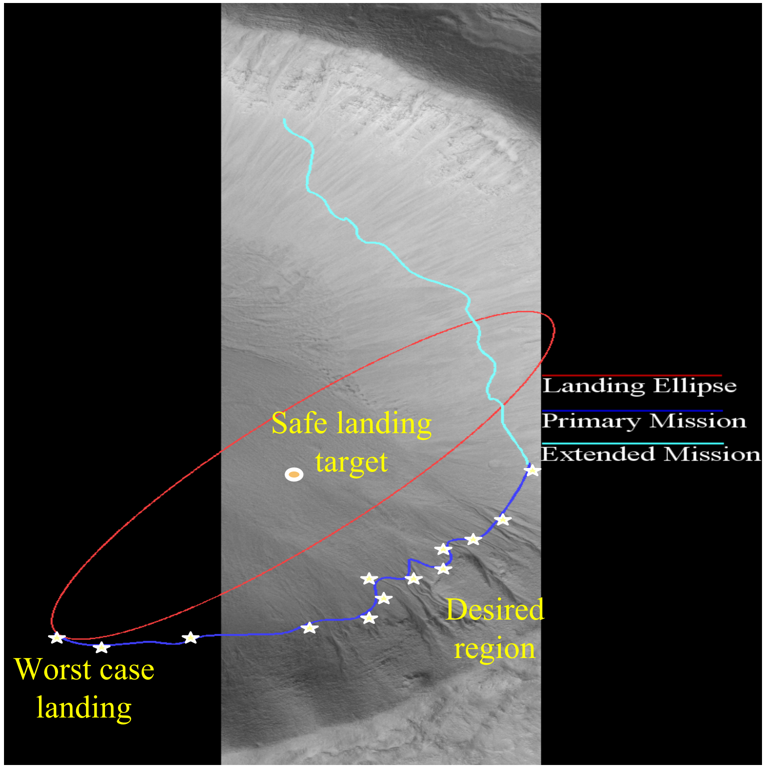
UT INVESTIGATIONS

- Develop a precision entry navigation filter to process IMU accelerometer data as an “external” measurement type
- Develop concepts for 3rd generation (precision landing) entry systems based on utilizing mixture-of-experts architecture processing inertial and relative measurements in real-time.





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ENTRY DYNAMICS VERIFICATION

- “Truth" trajectory generated with SORT, a NASA JSC entry guidance and navigation simulator.
- Assume the density, C_L, and C_D are precisely known.
- The differences in the trajectories due to different numerical integration algorithms and gravity models
  - A J_2 model is used in the filter dynamics model
  - NASA simulations utilize higher-order gravity models
- EKF filter residuals can be attributed almost entirely to uncertainty in the density and lift/drag models, hence there is a good possibility that the HME filter bank architecture can be used to detect optimal model parameters.

FLIGHT MODEL EQUATIONS

$$\dot{\mathbf{r}}_I = \mathbf{v}_I$$

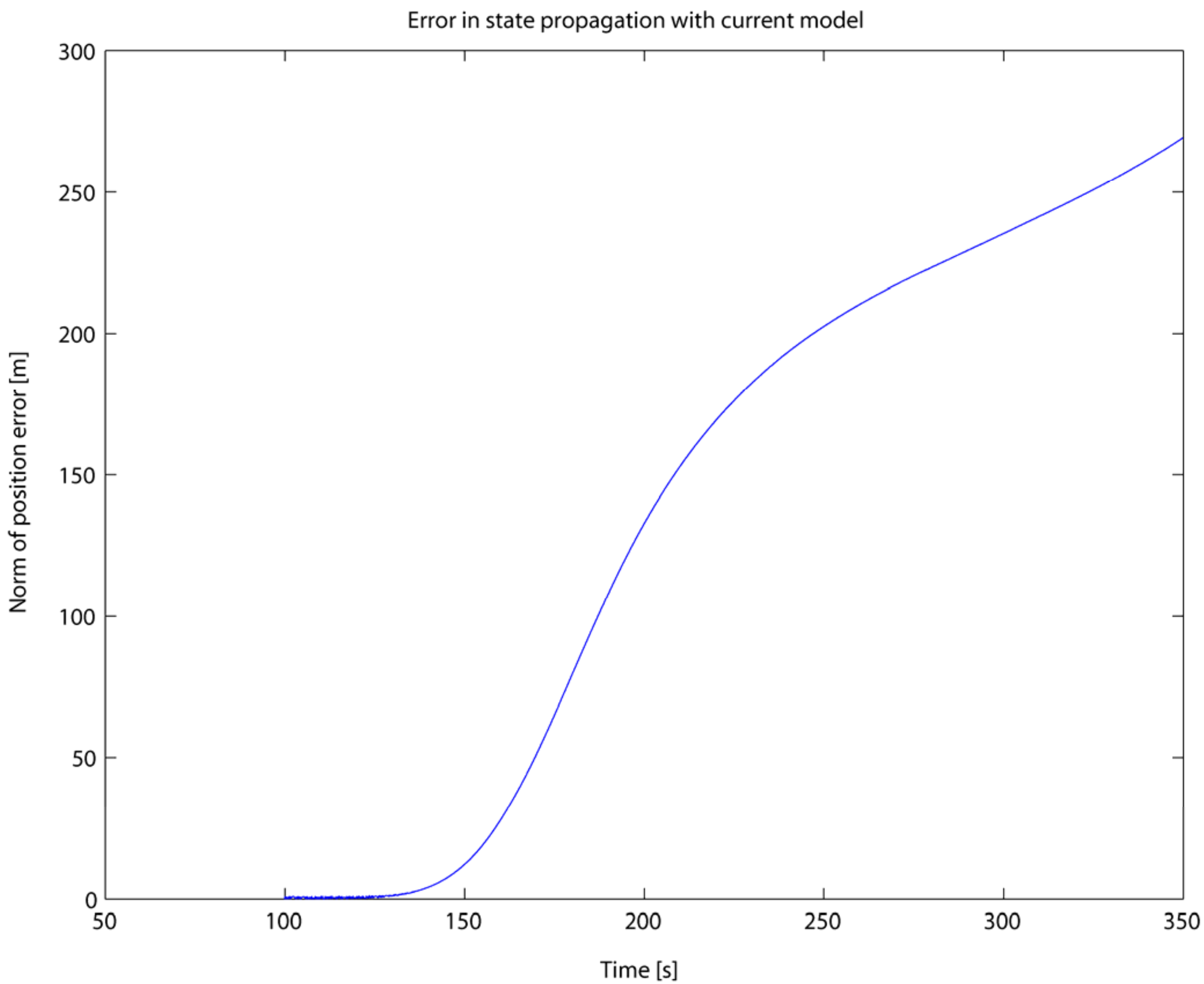
$$\dot{\mathbf{v}}_I = \mathbf{a}_I + \mathbf{g}(\mathbf{r}_I)$$

$$\dot{\mathbf{a}}_I = \left[\boldsymbol{\omega}^w \times \mathbf{a}_I\right] + \left[\dot{\varphi}\mathbf{e}_1^w \times \mathbf{a}_I\right] - \left[\dot{D}\mathbf{e}_1^w\right] + \dot{L}\left[-\mathbf{e}_2^w \sin\varphi + \mathbf{e}_3^w \cos\varphi\right]$$

$$\boldsymbol{\omega}^w = \frac{\mathbf{v}_r \times \dot{\mathbf{v}}_r}{V_r^2}$$

- These equations are used in a 9-state EKF.
- Performance has proven better so far than with a 6-state EKF (position and velocity only).

POSITION DIFFERENCE



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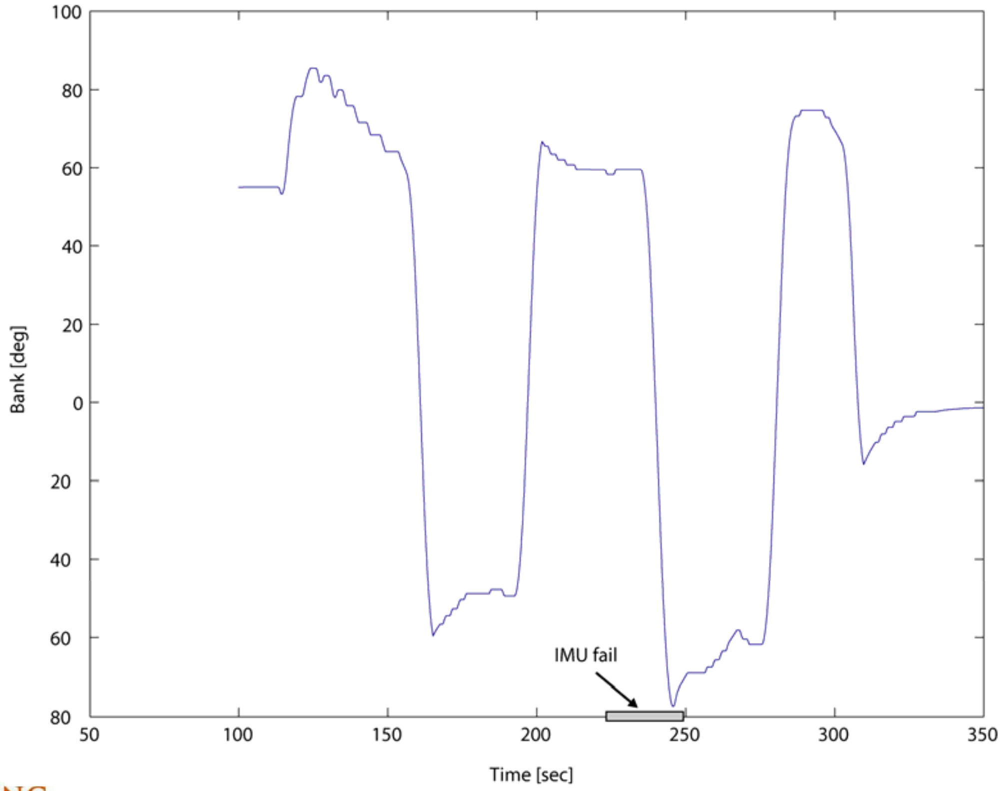
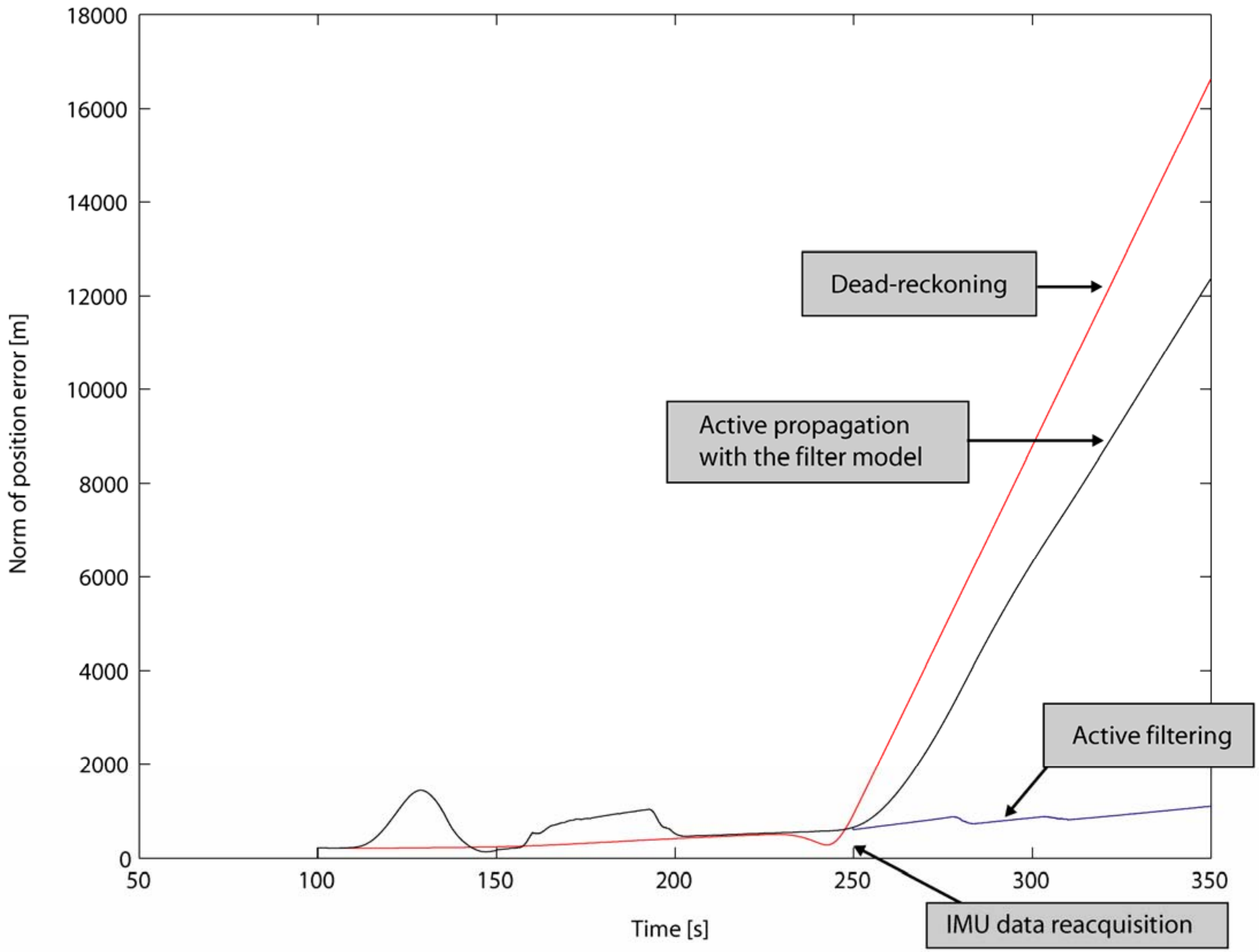
FILTERING VERSUS DEAD-RECKONING

- Single filter tested against dead-reckoning, including a simulated loss of measurement input, with and without eventual reacquisition.

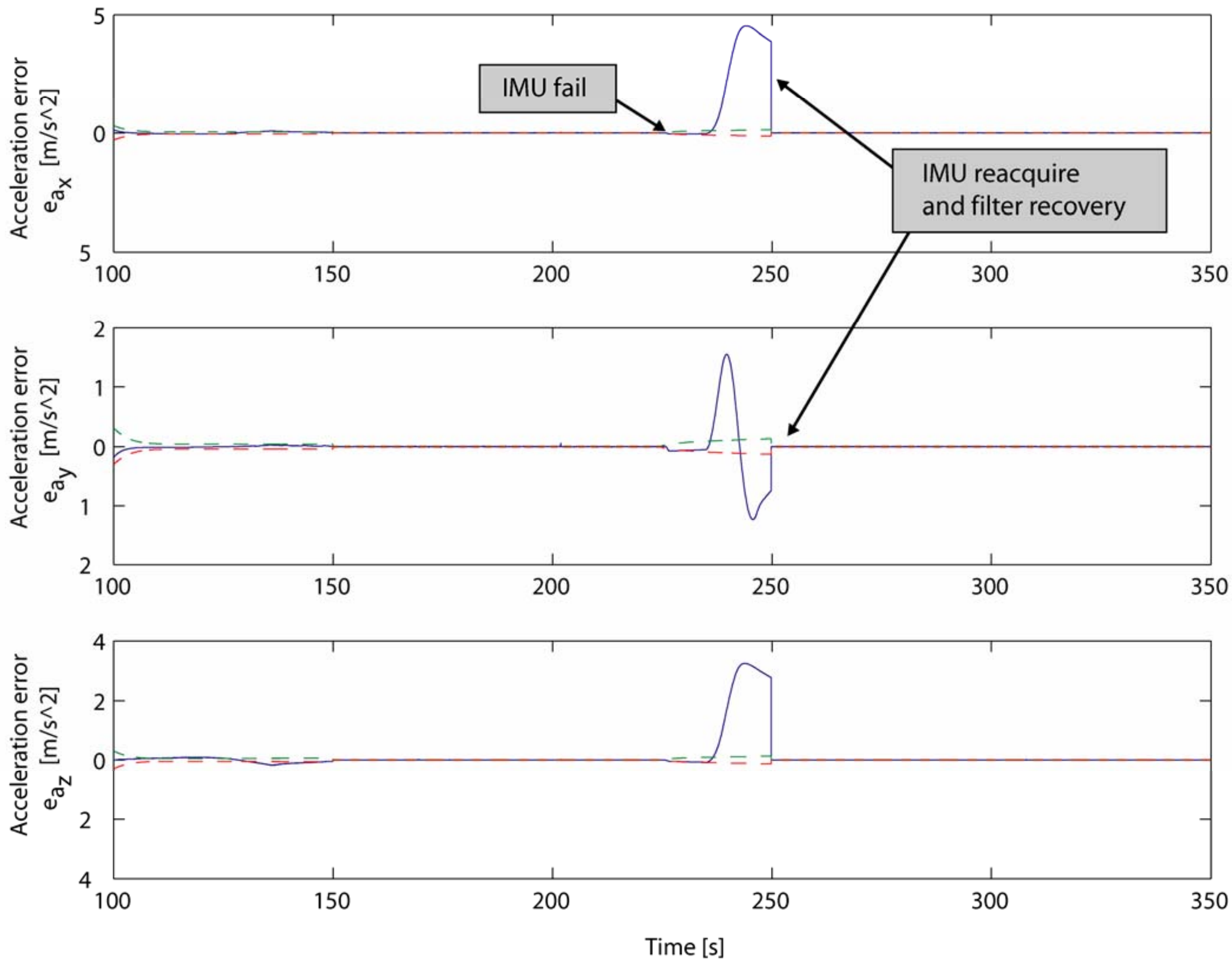
- The IMU fails at $t = 225$ seconds just before a bank maneuver.



DEAD-RECKONING VERSUS ACTIVE FILTERING



ACCELERATION ERRORS FOR IMU RECOVERY



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IMU RE-ACQUISITION

- Dead-reckoning:
  - Robustness to the lack of knowledge of environmental parameters is high since the process is not model dependent.
  - This is an open-loop process, hence estimation errors will always continue to grow without bound.
  - Cannot effectively react to IMU data loss since there is no way to reduce the state errors existing at the time of data reaquisition.
- Active Kalman filtering
  - Can lead to accurate recovery of the state estimate after IMU data loss and subsequent reacquisition.

ATMOSPHERIC DENSITY PROFILE

- The most likely use of the filter bank is in regulating filter banks parameterizing the atmosphere model.
- A two-layer exponential model is used as the base for each filter model (Tauber & et al.).
- Different models are created by varying the value of ρ_0 at the bottom of the layer.

$$\rho = \rho_0 e^{-\beta h}$$

$$h > 36Km \rightarrow \rho_0 = 0.03933Kg/m^3, \beta = 0.1181Km^{-1}$$

$$36 > h > 9Km \rightarrow \rho_0 = 0.01901Kg/m^3, \beta = 0.09804Km^{-1}$$

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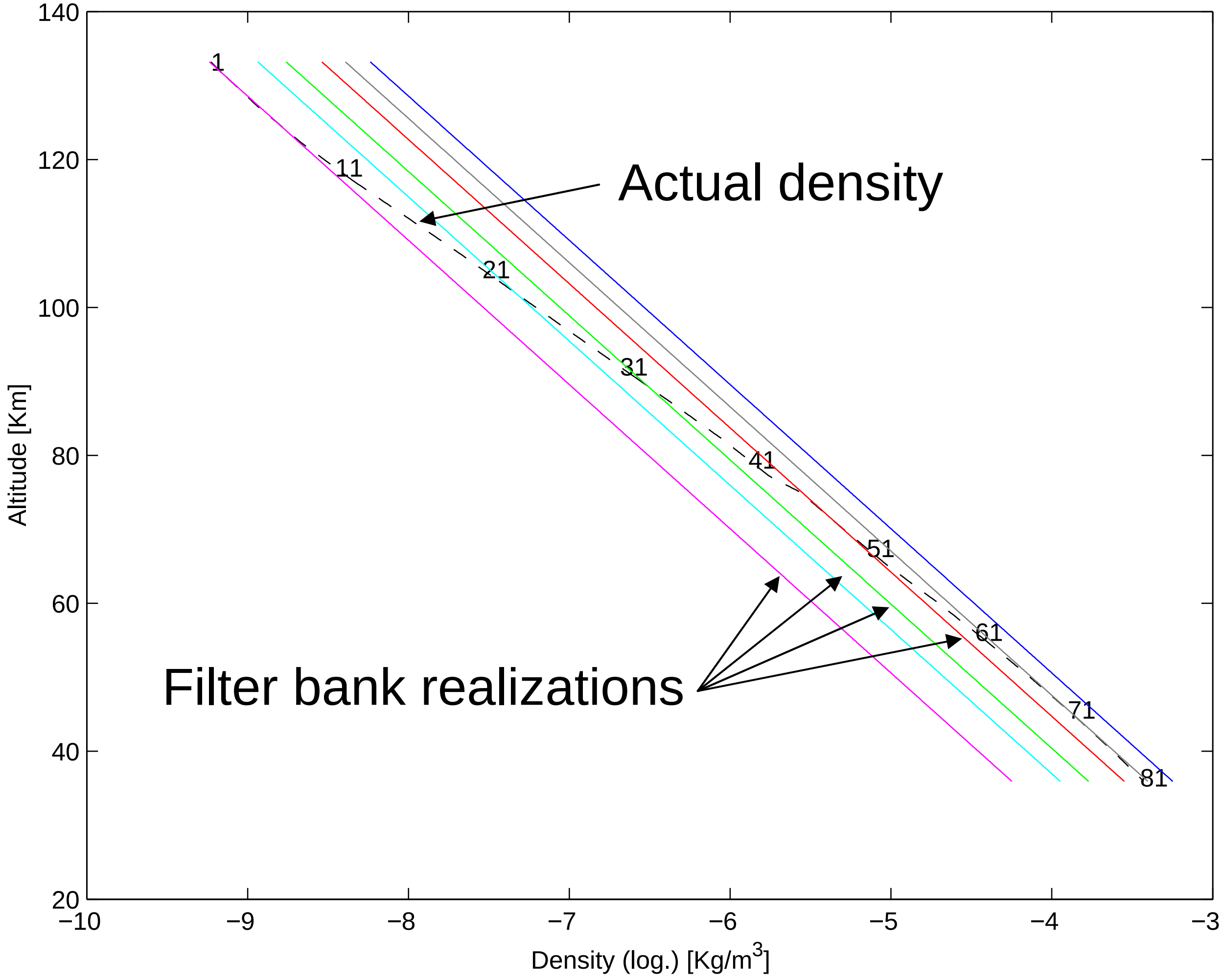
ATMOSPHERIC DENSITY PROFILE

- The value of ρ_0 is multiplied in each filter by the following factors.
- The color indicates which filters are represented on the following plots.

Filter	1	2	3	4	5	6
Color	blue	red	purple	green	gray	light blue
Coeff.	1	0.5	0.1	0.3	0.7	0.2

ATMOSPHERIC DENSITY PROFILE



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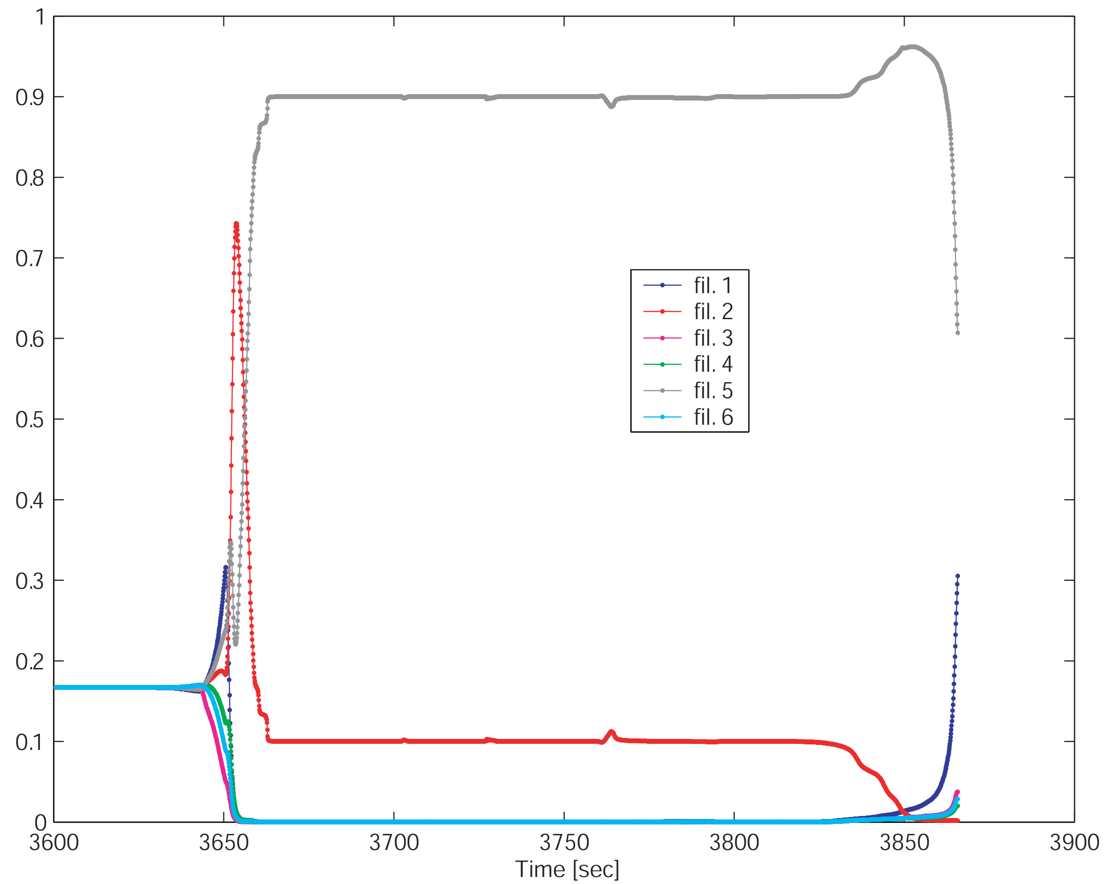
GATING WEIGHTS EVOLUTION



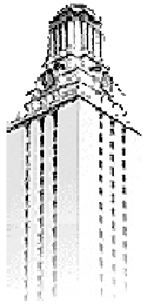
SUMMARY: HME EDL PERFORMANCE (1)

- Application of a hierarchical mixture of experts architecture to martian entry navigation during the highly dynamic hypersonic pre-parachute deploy phase was investigated.

- Proposed to utilize an approach that includes processing accelerometer and gyro data in an extended Kalman filter as if they were external measurements.

- A dynamics model suitable for use in an extended Kalman filter processing accelerometer measurements was developed and demonstrated to be an accurate representation of the entry dynamics in comparison with high-fidelity NASA simulations.

- Preliminary filtering results indicate that the entry navigation problem may be tractable using IMU accelerometer observations as measurements in an HME architecture.



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SUMMARY: HME EDL PERFORMANCE (2)

- In the event of intermittent IMU failure (that is, a failure to provide measurements for an extended period), an extended Kalman filter-based navigation algorithm is more robust and can, in fact, recover from the IMU data drop-out.

- Numerical experiments aimed at testing the ability of the HME to detect atmospheric parameters also provide positive indicators.

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Dr. P. Daniel Burkhart	

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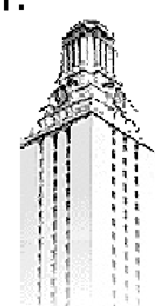

Filter bank

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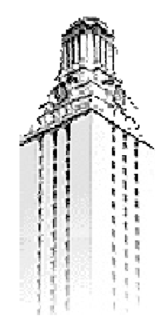

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