A Dynamic Data Driven Wildland Fire Model

The DDDAS Wildfire Team

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The Objective

A Dynamic Data Driven Application System (DDDAS) for short-range forecasts of wildfire behavior with models steered by real-time weather data, fire-mapping images, and sensor streams.
Goals

- **The model**
  - faster than real time
  - calibrated from measurements

- **Data assimilation: incorporate real data while the model is running**
  - sparse data (weather stations)
  - large image datasets (aerial photographs)
  - data acquisition steering
  - data arriving delayed and out of order
  - capable of adjusting a highly nonlinear model

- **Real-time visualization over the internet in the field**
Wildfire DDDAS Structure

Forecast

Model

Weather

Fire

Data Assimilation

Adjust

Compare

Interpret

Observation function

Synthetic data

Data Acquisition

Real data pool

Real time data

Aerial imaging

Sensors, telemetry

Weather data

Initial conditions

Map sources (GIS)

Fuel Data
Modular Software Structure: Major components are interchangeable

Model
1. NCAR coupled weather-fire model
2. Standalone PDE fire model (new), coefficients calibrated from measurements
3. Fire model coupled with WRF atmospheric model (future)

Data Acquisition
1. Simulated data
2. Weather data
3. Autonomous Environmental Sensors
4. Aerial images preprocessed for fire location

Data Assimilation
1. Ensemble Kalman Filter, improved efficiency
2. Improved morphing nonlinear filter (in progress)

Visualization
1. Matlab
2. Google Earth
The NCAR coupled weather-fire model
NCAR’s Coupled Atmosphere – Wildland Fire – Environment model (CAWFE)

**FIRE ENVIRONMENT**

- **Heat, water vapor, smoke**
- **Atmospheric Dynamics**
- **Fire Propagation**
- **Fuel moisture**
The standalone PDE based wildfire model
The standalone PDE based wildfire model

- Reduced chemical kinetics
- Balance of heat
- Balance of fuel supply
- Produces a correct traveling combustion wave
Simple Standalone PDE Fire Model

\[
\frac{\partial T}{\partial t} = \nabla (k \nabla T) - c_1 \cdot \nabla T - c_2 (T - T_a) + c_3 \frac{\partial S}{\partial t} \quad \text{(heat balance)}
\]
\[
\frac{\partial S}{\partial t} = -S f(T) \quad \text{(fuel balance)}
\]

\(T\) is the temperature
\(S\) is the fuel supply
\(f\) is the reaction rate function
\(T_a\) is the ambient temperature
\(\sigma\) is white noise

A simple model that however exhibits the correct qualitative behavior. Not captured yet: evaporation, multiple kinds of fuel and fire, interaction with atmosphere.
Numerical Method

- Upwinded finite differences
- Trapezoidal method in time
- Newton-Krylov (GMRES) in each time step
- Preconditioning by elimination of fuel variables eliminated at every node then FFT
- Mesh size $2m$, time step 1s
Time-Temperature Profiles

![Graph showing time-temperature profiles]

- Solid line: computed
- Dashed line: measured by a sensor passed over by a wildfire (Kremens et al, 2003)

The profile is used to calibrate coefficients in the model.
Further development of the PDE Fire Model

- **Refine the model**
  - conservation of heat in different kinds of fire (grass, brush, crown,…)
  - conservation of mass in different kinds of fuel (grass, sticks, logs…)
  - conservation of water contents in the fuels (evaporation)
  - Heat fluxes (convection, radiation) between the species. Non-local radiation transfer is expensive (integral operators).

- **Contemporary numerical methods**
  - Stabilized FEM, streamline diffusion, Discrete Galerkin..

- **Coupling with an atmospheric model**
  - Input wind, output heat and vapor fluxes
Data Acquisition
Autonomous Environmental Detectors

Primarily for local weather… but some burnovers

Data logger and thermocouples

Reconfigure to rapidly deploy
GPS - Position Aware
Versatile Data Inputs
Voice or Data Radio telemetry
Inexpensive

Autonomous Environmental Sensors

- positioned so as to provide weather conditions near a fire, are
- mounted at various heights above the ground on a pole with a ground spike
- will survive burnovers by low intensity fires
- the temperature and radiation measurements provide a direct indication of the fire
- front passage and the radiation measurement can also be used to determine the intensity of the fire
- the sensors transmit data and can be reprogrammed by radio
Wildfire Airborne Sensor Program (WASP)

Color or Color Infrared Camera
- 4k x 4k pixel format
- 12 bit quantization
- High quality Kodak CCD

Fire Detection Cameras
- 640 x 512 pixel format
- 14 bit quantization
- < 0.05K NEDT

High Performance Position Measurement System
- Position 5 m
- Roll/Pitch 0.03 deg
- Heading 0.10 deg
Processed Airborne Images

- Processed to extract the location and propagation vector of the fireline (Ononye, Vodacek, Saber, 2007)
- Three infrared bands combined to extract which pixels contain a signal from fire and to determine the energy radiated by the fire
Data Assimilation
Ensemble Kalman Filter (EnKF)

- Change the simulation state to balance two competing objectives:
  - The state should not change from the output of the model
  - The state should match the data

- The more uncertainty (bigger covariance) one of the conditions has, the more it can be violated (i.e., not be taken seriously) → **Least squares**

- Equivalent to: minimize in the span of the ensemble the sum of
  - Difference from forecast mean
  - Difference of the output of the observation function from the data
  - Weighted by the inverse of the covariance matrices

- There are other variants. But: in all variants, the analysis ensemble is always a linear combination of the members of the forecast ensemble.

- Dominant operations:
  - advance ensemble members in time, embarrassingly parallel
  - dense linear algebra (parallel, e.g., Scalapack)
But Ensemble Kalman Filter fails for the wildfire problem

- The analysis (=output) ensemble from EnKF is made only out of *linear combinations* of the forecast (=input) ensemble so if the forecast ensemble is not rich enough, the linear combination cannot approximate the analysis state well → nonphysical states

- Probability distributions are *strongly non-gaussian* (burning/not burning)

- Discrepancies are in the fireline position as well as in the intensity
What are we doing about it:
New developments in EnKF

- Prevent nonphysical states:
  **Penalization, regularized EnKF**

- Nongaussian distribution:
  **Predictor-corrector filters**

- Position errors:
  **Morphing filters**
The Reference solution represents the truth. Data assimilation by a standard ENKF algorithm results in an unstable solution because of the nonlinear behavior of wildfire. Stabilization gives the regularized solution ENKF+reg. Without data assimilation, the solution would develop as in the Comparison; the data assimilation shifts the model towards the truth. The model state is a probability distribution, visualized in the two ENKF figures as the superposition of transparent temperature profiles of ensemble members.
Dealing with position errors:
Morphing Ensemble Filters
interpolate between two maps: \( f_{\lambda}(x) = f(x + \lambda T x) \)
given \( f = f_0 \) and \( g = f_1 \), how to find \( T \) ?
solve minimization problem for registration distance
\[
d(f, g) = \min_T \| f \circ (I + T) - g \| + \| T \| + \| \Delta T \|
\]
can be done by multilevel optimization, reasonably fast

The transformation is found automatically without any human input.

(Picture Gao and Sederberg, 1998)
Automatic Morphing of Fire Positions
Morphing Ensemble Filter

- Represent the ensemble members as *morphs of one fixed state plus a residual*:
  \[ u_i = (u + r_i) \circ (I + T_i) \]

- **run the EnKF on the morph mappings** \( T_i \) **and the residuals** \( r_i \) **instead of the states** \( u_i \)

- After the members are advanced in time, use the previous morph mappings as a good initial guess.

- **Now the EnKF can move the fireline easily!**
Data Assimilation by Morphing EnKF

Forecast fire position (model output)

Data

Analysis fire position (data accounted for, continue running the model)

Instead of having linear combinations of the states create a number of smaller fires, linear combinations of the transformed states move a single fire around.
Google Earth Visualization
To Do: Put it All Together and Test on a Real Fire

- The morphing EnKF method works reliably now – integrate it into our production quality data assimilation framework
- Integrate the data assimilation code with the real wildfire-atmosphere code
- Connect the input with real-time data acquisition, under development separately
- Integrate the output with Google Earth visualization
- Test on reanalysis of the Esperanza 2006 fire
Esperanza Fire, Riverside County, CA
October 26, 2006

- **Satellite data**
  - Landsat image, false color obtained ~11:00 am, about 10 hours after the fire started

- **Aerial data**
  - FireMapper images on Oct. 26, two on Oct 27, and one on Oct 28.
  - Collaborator: Phil Riggan
    http://www.fireimaging.com

- **Weather:**
  - 3 RAWS weather stations within the overall modeling domain, 10 RAWS stations in Riverside County
    http://raws.wrh.noaa.gov/roman/
  - Archived global weather data

- **Other:**
  - Fuel maps, incident reports, daily fire perimeter maps, etc. (State of California, USDA Forest Service, etc.)
Conclusion

- Dynamic Data Driven Application System for wildfire modeling and prediction in progress
- Highly nonlinear system poses unique challenges in data assimilation and motivates new developments in data assimilation methodology
- Practical needs drive new mathematical methods
- Collaborative software development
- Emphasis on software validation and reliability
- Coupled atmosphere-fire model handles realistic fires
- Many components done, still need to put them together
- Data assimilation works well on model fire problems