Improving Environmental Forecasts using Remote Sensing Data Assimilation

Anthony Vodacek

*Digital Imaging and Remote Sensing Laboratory (DIRS)*

*Center for Imaging Science*

*Rochester Institute of Technology*

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Overview

• Digital Imaging and Remote Sensing Laboratory
  – research areas and capabilities
  – hardware
• Data Assimilation and Dynamic Data Driven Application Systems
• Beach Closure Application
• Wildland Fire Application
Digital Imaging and Remote Sensing Laboratory (DIRS)

DIRS consists of

• 5 full time faculty
• 7 full time research staff
• 1 post-doctoral fellow
• 1 administrative assistant
• 6 undergrad research assistants
• 9 MS candidates
• 22 Ph.D. candidates

Current research program

• 26 funded projects
• annual research ~ $2M

Sponsors from government and industry
Hyperspectral Imaging Concept: target detection
DIRSIG: The Digital Imaging and Remote Sensing Image Generation Model
A physics-based ray tracing model for generating synthetic remote sensing scenes

near infrared simulation of a section of the RIT campus

RGB simulation of a section of Rochester
Modular Imaging Spectrometer Instrument (MISI)

false color image of Lake Ontario shoreline
WASP and WASP Lite airborne systems
mosaic of RGB camera images

WASP

thermal infrared camera image
Data Assimilation versus Dynamic Data-Driven Application System

“…the ability to dynamically incorporate additional data into an executing application, and in reverse, the ability of an application to dynamically steer the measurement process”
The synthetic data generation is an important aspect of data assimilation and may or may not be complicated to produce.
Dynamic System and Data Assimilation

• System model
  – Describes how the state of the system evolves over time

\[ x_t = Ax_{t-1} + w_{t-1} \]

• Measurement model
  – Describes how measurements are related to state variables - “synthetic data”

\[ \rho_t = Hx_t + v_t \]
### Kalman Filter Operation Cycle

**Time Update (Prediction)**

1. Predict the state variable
   \[ \hat{x}_t^- = A\hat{x}_{t-1}^+ \]

2. Predict the system uncertainty
   \[ P_t^- = AP_{t-1}^+A^T + Q_{t-1} \]

**Measurement Update (Correction)**

1. Compute the Kalman gain
   \[ G_t = P_t^-H^T(\hat{x}_t^-)[H(\hat{x}_t^-)P_t^-H^T(\hat{x}_t^-) + N_t]^{-1} \]

2. Update estimate with measurement
   \[ \hat{x}_t^+ = \hat{x}_t^- + G_t\left[\rho_t - H(\hat{x}_t^-)\right] \]

3. Update the system uncertainty
   \[ P_t^+ = (I - G_tH(\hat{x}_t^-))P_t^- \]

Initial estimates for \( x \) and \( P \)

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Welch, G. and Bishop, G. (2006) *An introduction to the Kalman Filter*. Department of Computer Science, University of North Carolina at Chapel Hill.
Integrating remote sensing with water quality modeling for prediction of beach closures at Ontario Beach, Rochester NY
Image Data: MODIS
1 km pixels
Image Data: Landsat
30 m pixels
Lake Ontario

- very clear water
- suspended sediment
- colored dissolved organic matter
- lots of algae
Case Study: Public Beach Closures

1. Swimming season 2003: June 21 ~ Sep. 1
2. Beach open 48 days (66%)
3. Closed 25 days (34%)
4. Water quality impacts on beach
   - Sediment dominated plume
   - Wind and lake currents can push polluted plume water onto the beach
   - Poor water clarity
   - Prior day bacterial counts
   - Local rainfall
   - Excessive algae

Goal: Steer measurement and management efforts, capture expert knowledge

MODIS 250 m Surface Reflectance Data (645 nm) (Aug. 18, 2003)

August 18, 2003 – beach closed due to westward flowing plume
MODIS Reflectance Images showing river plume, with beach closings and wind direction indicated.

False-color image (R: 858 nm G: 645 nm B: 645 nm) Vegetation appears red, water appears dark, and plume appears blue.
Modeling System Overview

Weather variables
- Air/Dew point temperature
- Wind speed/direction
- Cloud cover/height
- Precipitable water
- Pressure

BASINS HSPF

TSS & CDOM concentration and discharge

ALGE

Updated TSS concentration profiles

HydroLight

3D TSS & CDOM concentration profiles

EnKF

Modeled $R_{rs}$

MODIS 250 m reflectance data

Updated TSS concentration profiles

MODIS 250 m reflectance data

Updated TSS concentration profiles

Modeled $R_{rs}$
Hydrodynamic model:
whole lake simulation nudges local plume simulation

Lake Ontario bathymetry and current vectors

Genesee River sediment plume

TSS concentration (g/m³)
Radiative transfer model: synthetic image generation

- Absorption and scattering
- Chlorophyll and CDOM concentration vertical profiles

3D suspended sediment concentration

HYDROLIGHT

Modeled $R_{rs}$
remote sensing reflectance at 645 nm
EnKF estimate from river mouth pixel

**Graph:**
- **Y-axis:** TSS concentration (g/m$^3$)
- **X-axis:** Date
- **Legend:**
  - Ensemble model states
  - EnKF estimate
  - Truth (USGS)
EnKF estimate error for TSS at the river mouth

1. Error of the KF estimates decreases with a measurement update
2. The KF estimates deteriorate until new MODIS data become available

Red rectangles indicate a day MODIS data is available for updating.
Comparison of spatial estimate of plume
So, is this useful?

- Calculate the average TSS in front of beach
- A threshold of 45 mg/L provides a reasonable decision boundary for open/closed
Future Water Quality Work

• Better weather data (lake breeze):
  – GLOS station
  – commercial aircraft profiles
  – mesoscale weather forecast

• Include the variability of model parameters and adjust the parameters based on the assimilation results
  – Particle density and diameter
  – Some physical parameters

• Assimilate other satellite/airborne data and field observations into the hydrodynamic model as well
  – MODIS Thermal (1 km, day/night)
  – Landsat series
  – RIT has 3 airborne sensors

• Increase the number of ensemble members to improve the estimation accuracy

• Better error estimates

• Other data assimilation approaches
Wildland fire propagation
ITR/NGS: Collaborative Research: DDDAS: Data Dynamic Simulation for Disaster Management

CSR-CSI: Collaborative Research: Dynamic Sensor/Computation Network for Wildfire Management
Fire radiation peaks in the midwave IR
Fire images captured with the RIT WASP Lite sensor of a prescribed burn in Kentucky in April 2007

**panchromatic**

**thermal infrared**
(microbolometer)
WASP daytime images of a wildfire in Montana (orthorectified)

Short wave infrared

Mid wave infrared - low gain
Fire Propagation Modeling System

- atmosphere-fire model
- data transmission and visualization
- update
- output

EnKF

- synthetic sensor and image data
- ground sensors and airborne imagery
Image processing methods for fire features: assimilating extracted information

automated extraction of fire line parameters


Estimating the infrared scene radiance requires 3 phenomena to be modeled using DIRSIG:

1. Radiation from the hot ground under the fire front and the cooling of the ground after the fire front passes.

2. The direct radiation to the sensor from the 3D flame.

3. The radiation from the 3D flame that is reflected from the nearby ground.

Surface temperature maps with cooling

16 minutes after ignition

74 minutes after ignition
Final rendering: synthetic infrared scene of a grassfire at night

WASP images (zoom) of a forest fire in Montana during the daytime
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