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Title

Model Based Multiscale Sensing (MAS 5)

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Authors

Cathy Kong William Kaiser Greg Pottie

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S Center for Embedded Networked Sensing

Model Based Multiscale Sensing

Xiangming Kong, William J. Kaiser and Gregory J. Pottie

Motivation

Multiscale Sensing: Combining hierarchy of sensor data sources with varying deployment density and sensing modes

Three-phase Information Processing

- Decompose sunlight into 3 components

- Model validation and updating phase

available model in the model set

Direct beam, sky diffused light and leaf diffused light

· Build a set of incident light distribution and reflectivity models

- Model learning phase

– Model selection phase

reflectivity distributions

- Problem: Achieve the high fidelity of exhaustive sensing by engaging multiple levels of sparse sensing
- Application: Determine spatiotemporal characteristics of sunlight field under forest canopy
- Motivation for Model Based Approach:
 - Direct fusing of measurements at multiple levels enhances performance, but improvement benefit is limited
 - Models directly extract phenomena behavior
 - Communication and computation rate requirements constrained to most important data
 - New information can be directly incorporated by updating models

Multi-level Information Processing

• Information Levels

- Context: weather condition and environment
- High level information: camera provides global measurement with low accuracy and high spatial resolution
- Low level information: PAR sensor provides local measurement (low spatial resolution) with high accuracy
- Image Processing

· Apply dense sampling in different small areas to learn the possible incident light distributions and

- Obtain distribution model of sky diffused light and leaf diffused light from measured data

· Compare the reflected light distribution model measured by the camera with the set of models

• Verify the PAR sensor measurement matches the selected incident light distribution model

· Bound the minimum number of PAR sensors to fulfill the model selection and validation task

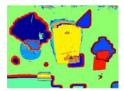
• Update the model set if the measured incident light distribution model is substantially different from any

- Obtain distribution models of direct beam from measured and simulated field · Combine the two to build a set of reflected light distribution models

· Select a few models from the model set that are closest to the measured model · Use static PAR sensor measurement to pick one most probable model

- Segment the field image into feature clusters
- Partition the field based on pixel features and connectivity





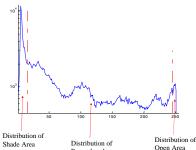


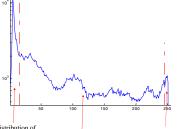
Partitioned Patches in Pseudocolog





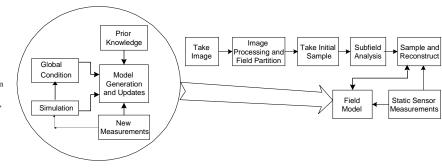
Similar reflectivity, different incident light ntensity





Open Area Penumbra Area

- · Interactive Information Processing
 - Simulate the field with parameters based on prior knowledge and global condition
 - Refine the simulation parameter with information from static sensor measurements
 - Update models by assimilating new simulation results, static sensor measurements and reconstructed field



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