Multiscale Analysis of Multimodal Imagery for Cooperative Sensing

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DDDAS PI Meeting
30 Sept – 2 Oct 2013

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Haibin Ling – Temple University

Collaborators:
K. Palaniappan – University of Missouri
Zhi (Gerry) Tian – NSF, Michigan Tech
Khanh Pham – AFRL/RV (other AFOSR task – Game Theory)
OUTLINE

• Cooperative Sensing
  • Links to Information Fusion
  • Track and ID
  • Cloud Computing
    Erik Blasch
• Multimodal Imagery Sensing
  • 3D Challenges
  • Persistent Appearance models
    Guna Seetharaman

Theory
  Dynamic Tracking

Software
  Big Data Analysis

APPLICATION
  Aerial Surveillance

Theory
  3D Modeling

Software
  Multicore
Accomplishments Yr1

• Six papers highlighting DDDAS motivations
  • Sent to IEEE Mag: DDDAS Cloud-enabled robotics
  • Modeling (track&ID), Software (Cloud), Application (ISR)

• Hosted of three faculty members, 2 students

• IEEE Distinguished Lecturer (one with RIT)
  • Updated Situation Awareness Tutorial with DDDAS

• Four applications of DDDAS
  • Cloud Computing, Information Fusion - Enterprise Modeling
  • Visualization, Simultaneous Tracking and ID

• One research award, hosting 2 conferences
  • NOTE: AIAA/IEEE DASC, Oct 2014 (Colorado Springs – UAVs)

Erik Blasch

Blasch/Seetharaman – DDDAS Review 2013
• Version 1

From Alex Aved
• Version 2

From Alex Aved
Special Journal

• Special Issue in IEEE Magazine
  IEEE Transactions on Emerging Topics in Computing
  http://www.computer.org/portal/web/tetc
  Special Issue on Emerging Computing Technologies for Resilient and Robust Intelligent Infrastructure
  Special Issue on Emerging Systems and Applications for Wireless Health Computing
  Special Issue on Advances in Semantic Computing
  Special Issue on Coordination in Large-scale Socio-Technical Systems - MAY
  Special Issue on Advances in Neuromorphic and Analog VLSI Computing - JUN
  Special Issue on Emerging Mobile and Ubiquitous Systems – JUL
OUTLINE

• Motivation

• DDDAS Concept for Multi-Modal Cooperative Sensing
  • DDDAS match with Information Fusion to Visualization
  • DDDAS rich with applications to complex environmental modeling

• Information Fusion – Surveillance, Target Tracking
  • Developments in motion imagery with large-data formats
  • Focused on target tracking: need environment model in WAMI
  • DDDAS for Simultaneous Tracking and Identification

• DDDAS With Cloud Computing applications
  • Statistical Mathematical modeling for Robotics applications
  • Developing results over different applications

• Summary: Future reporting in 2014 WAMI text
• Motivation

• Using the DDDAS concept (*mathematics, modeling, and software*); information fusion systems composing multi-modal sensor measurements can be enhanced to consider current trends in big data (*e.g.* *large imagery*), enterprise architectures (*e.g.* *dynamic*), and systems management for real-time cooperative sensing.

• The novelty of the work consists of developing a statistically optimal image perspective formation using 3D homographical mappings applied to *Wide Area Motion Imagery* for scene characterization, target tracking, and situational awareness.

• Applying the advanced scene characterization software in the AFRL PCPAD-X (*Planning & Direction, Collection, Processing & Exploitation, Analysis & Production, and Dissemination eXperimentation*) Program - that consists of multi-intelligence data fusion from streaming full-motion video (*IMINT* - *Image*) and operator textual reporting (*HUMINT* – *human*), the emerging situation can be understood for real-time mission management.
Dynamic Data Driven Application Systems (DDDAS)

- Multi-scale Multimodal Data
- Full Motion Video
- Sensor Management
- Object ID and Tracking
- Filtering
- User Refinement
- Simulations
- Operational Condition Fidelity
- Mission Management
- Measurements
- Situation Assessment
- Forecasting, Prediction
DDDAS Background

• Other works of interest

  • DDDAS since its inception has been applied to numerous areas where complex real-world conditions are not predetermined by initialization parameters and data
  
  • DDDAS is related to Information Fusion in processing stochastic information

  • DDDAS applied to Environmental modeling, Situation awareness, and Systems-level applications

• Environmental modeling

  • Oceans [Patrikalakis, 2004], Wildfires [Chen M, 2005]
  
  • Transportation [Fujimoto R. M; 2004], emergency medical response [Gaynor M; 05]

  • Waste distribution [Parashar, M, 2006; Mahinthakumar, K, 2006].

  • Collaborative Adaptive Sensing of the Atmosphere (CASA) (Radar) formed by the National Science Foundation [Brotzge, J., 2006].
Figure 1: Diagram of DDDAS Interactions

Suggested Updates

**Scenarios**

- **Theory**
- **Measurements**

- **Software**
  - Management
  - Interaction

- **Analytics**
- **Control**

- **Visualizations**
- **User**

- Models
- Data

**DDDAS 2010**
DDDAS

Links to Information Fusion

Information Fusion Levels

1. Estimation
   - Tracking
   - Pattern Rec.

2. Analytics
   - Situation Awareness

3. Models
4. Data
5. Control
6. Scenarios

Theory

Measurements

Software

Visualizations

User

Interaction

Management
DFIG - Fusion Model
Target Tracking (L1) to User Refinement (L5)

Information Fusion and DDDAS

- **Information Fusion**
  - **Processing Levels:**
    - L0 data registration,
    - L1 object assessment, (tracking, classification)
    - L2 situation awareness
    - L3 impact assessment (threat)
    - L4 process refinement,
    - L5 user refinement
    - L6 mission management

- **DDDAS and Information Fusion**
  - **Environmental modeling** for object assessment, situation and impact assessment over mission needs
  - **Applications:** emergency response, sensor /user control (CASA), transportation. → HERE, focused on ISR tracking in imagery

Visualization Software


• JView – Java Viewer (User Defined Operating Picture)

• Visualization comprised of three transforms (Force Grid, Filter, and Time Filter), a Renderer (Slice Volume Renderer), and a data access component (JDBCTable)
JView - User Defined Operating Picture


- **Layered Visualization** For Large Data
  - Space
  - Air
  - Land

Weather
JView - User Defined Operating Picture


- Layered Visualization For Large Data
- Situation Awareness

SSA: Space

Air-Land SAW
JView - User Defined Operating Picture


• Layered Visualization For Large Data
• Combined View

Global - SAW

CUNE – UAV Network
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Fusion and Estimation

• Optimal Methods
  • Bayesian
    • Fusion Methods (Multi-INT data – Non Linear)
      • Odds Likelihood
      • Neural Nets/Fuzzy Logic/Expert Systems
      • Evidential Reasoning
    • Interactive Models (Multiple Models – Non Gaussian)
      • IMM – weight a series of models based on the measurement (Gauss)
      • MMAE – Multiple Model Adaptive Estimation (Gauss)
      • GSM – Gaussian Sum of Mixtures (Gauss)
      • PF – Particle Filtering
      • IMM-RUT – Random Unscented Transform
Information Fusion and DDDAS

• **DDDAS**
  - Supports large (complex) data processing
  - Reasons over stochastic uncertainty
  - New Application: *Enterprise Intelligence, Surveillance, and Reconnaissance*

• **Information Fusion**
  - Sensor Fusion (sensing)
  - Info Fusion (enterprise)
  - User Interaction (Report)
Point of View

Point of View:
Perceptual Video Processing: Seeing the Future!
CLIF 2006/2007


RY-09-0449
**Complex Scene Analysis**
- **Data**: Text (analyst reports) - “Find Building A”
- **Data**: Geospatial (terrain) - “3D surface”
- **Dynamic**: Perspective change from moving camera

**Surface Mapping**
- **Simple**: 2D surface homography
- **Complex**: Different surfaces in 3D
- Least Squares corrupts 3D result

**Science Contribution**
- Locate primitive surfaces
- Determine dynamic change through mixture of piecewise optimize mappings
WAMI Modeling

- Complex Imagery
- Changing Dynamics
- Model → testing, and update
- Decisions –
  - Terrain Information (environment)
  - Man-made objects
    (Buildings, targets)

WAMI Modeling

WAMI MODEL → Vanishing Point $(\ell_x, \ell_y)$ → H-Test $H0 / H1$ → Edges

DDDAS Applications Modeling (1)
Multimodal Edge Detection

WAMI

Wide-Area Motion Imagery

Environment

Vanishing Point

EW Road

$[\ell_x, \ell_y, \ell_z]$

Road

Blasch/Seetharaman – DDDAS Review 2013
Multimodal Inputs (only WAMI displayed)

- Text (analyst reports)
- Geospatial (terrain)
- Use primitives (through vanishing points)

Multimodal Difficult

Text: “Find building A”

Environment
Vanishing Point

Target
Vanishing Point

WAMI
Wide-Area Motion Imagery

DDDAS

EW Road

[ℓ_x, ℓ_y, ℓ_z]
DDDAS Mathematics and Stat Modeling
Measurement based Optimality

Non-Homography relation Transforms (between multimodal collections)

\[ f(x, y; t) \xrightarrow{c \in S \in a} f(x', y'; t + 1) \]

Surface (S1)
(e.g. tennis court)

Line (S2)
(e.g. telephone pole)

Wall (S3)
(e.g. fence)

Cube (S4)
(e.g. building)

COMPLEX
(e.g. City)

Homogeneous
\[ z = -px - qy - s \]

\[ x' = \frac{a_1^5x + a_2^5y + a_3^5}{a_7^5x + a_8^5y + a_9^5} \]

\[ y' = \frac{a_4^5x + a_5^5y + a_6^5}{a_7^5x + a_8^5y + a_9^5} \]

\[ s = \text{each surface} \]

\[ L = \text{direction cosine} \]

\[ L_{34} = S_3 \in S_4 \]

Mathematical Issues Working
- Must have tangential conformity
- Optimality Conditions (from terrain)
- If Imagery, how other sensors
- Joint DDDAS optimization
Collaboration: RY (Sensors), RI (Information), RH (Human Effectiveness)
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Bayes Theorem

\[ P(h|D) = \frac{P(D|h) P(h)}{P(D)} \]

- \( P(D) \): prior probability of the data D, \textit{evidence}
- \( P(h) \): prior probability of the hypothesis h, \textit{prior}
- \( P(h|D) \): posterior probability of the hypothesis given the data D, \textit{posterior}
- \( P(D|h) \): probability of the data D given the h, \textit{likelihood} of the data

By observing the data D we can convert the prior probability \( P(h) \) to the a posteriori probability (posterior) \( P(h|D) \).

The posterior is probability that h holds \textit{after data D has been observed}.

The evidence \( P(D) \) can be viewed merely as a scale factor that guarantees that the posterior probabilities \textit{sum to one}.

Revisiting with DDDAS
DSMT Fusion
Proportional Conflict Redistribution (PCR5)

\[
\Theta = \{A, B\}
\]

Shafer’s model

\[
\begin{array}{|c|c|c|}
\hline
 & A & A \cup B \\
\hline
m_1(.) & 0.6 & 0.1 \\
m_2(.) & 0.2 & 0.3 \\
m_{12}(.) & 0.44 & 0.27 \\
\hline
\end{array}
\]

\[
k_{12} = m_{12}(A \cap B) = m_1(A)m_2(B) + m_1(B)m_2(A) = 0.18 + 0.06 = 0.24
\]
different from previous examples

\(m_2(A) = 0.2\) and \(m_1(B) = 0.3\) did make an impact on the conflict because \(m_2(A)m_1(B) = 0.2 \cdot 0.3 = 0.06\) was added to the conflicting mass. So, \(A\) and \(B\) are involved in the conflict (\(A \cup B\) is not involved), hence only \(A\) and \(B\) deserve a part of the conflicting mass, \(A \cup B\) does not deserve.

Let \(x_1\) be the conflicting mass to be redistributed to \(A\), and \(y_1\) the conflicting mass redistributed to \(B\) from the first partial conflicting mass 0.18, and similarly for \(x_2\) and \(y_2\) with partial conflict 0.06; one has:

\[
x_1/0.6 = y_1/0.3 = (x_1 + y_1)/(0.6 + 0.3) = 0.18/0.9 = 0.2
\]

\[
x_2/0.2 = y_2/0.3 = (x_2 + y_2)/(0.2 + 0.3) = 0.06/0.5 = 0.12
\]

Fusion results

\[
\begin{array}{c}
x_1 = 0.6 \cdot 0.2 = 0.12 \\
y_1 = 0.3 \cdot 0.2 = 0.06 \\
x_2 = 0.2 \cdot 0.12 = 0.024 \\
y_2 = 0.3 \cdot 0.12 = 0.036
\end{array}
\]

\[
\begin{array}{|c|}
\hline
m_{PCR5}(A) = 0.44 + 0.12 + 0.024 = 0.584 \\
m_{PCR5}(B) = 0.27 + 0.06 + 0.036 = 0.366 \\
m_{PCR5}(A \cup B) = 0.05 + 0 = 0.05 \\
\hline
\end{array}
\]

With DSmH and Dubois & Prade’s rules

\[
\begin{array}{c}
m_{DSmH}(A) = m_{UP}(A) = 0.44 \\
m_{DSmH}(B) = m_{UP}(B) = 0.27 \\
m_{DSmH}(A \cup B) = m_{UP}(A \cup B) = 0.29
\end{array}
\]

With Dempster’s rule

\[
\begin{array}{c}
m_{DS}(A) \approx 0.579 \\
m_{DS}(B) \approx 0.355 \\
m_{DS}(A \cup B) \approx 0.066
\end{array}
\]

DMST Tutorial : Jean Dezert, 2008
**PCR5 Tracking and ID**


- **Advancement in Modeling**

  - When prior’s are not uniform, Dempster’s rule is not consistent with Bayes’ Rule. Let \( m_0 (X) = P(X), [\text{not in DS}], \)

    \[
    m_1 (X) = P(X | Z_1), \text{ and } m_2 (X) = P(X | Z_2), \text{ then}
    \]

    \[
    m(X) = \frac{m_0 (X) m_1 (X) m_2 (X)}{1 - m_{012} (\emptyset)} = \frac{P(X) P(X | Z_1) P(X | Z_2)}{\sum_{i=1}^{N} P(X_i) P(X_i | Z_1) P(X_i | Z_2)}
    \]

- **Solution**

- **Proportional Conflict Redistribution rule no. 5 (PCR5)**

    \[
    m_{\text{PCR5}} (X) = \sum_{X_1; X_2 \in 2^\Theta} m_1(X_1) + m_2(X_2) \quad + \quad \sum_{X_2 \in 2^\Theta} \left[ \frac{m_1(X_1)^2 m_2(X_2)}{m_1(X_1) + m_2(X_2)} + \frac{m_1(X_1) m_2(X_2)^2}{m_1(X_1) + m_2(X_2)} \right] 
    \]

    \[
    X_1 \cap X_2 = X \
    X_2 \cap X = \emptyset
    \]
Advancements in Estimation Modeling (PCR5)

Tracking and identification of two objects. $CM = \begin{bmatrix} 0.75 & 0.25 \\ 0.25 & 0.75 \end{bmatrix}$. (Low confusion), but gets better

$DS \approx= \text{Bayes}$

Reacts Faster


• Advancements in Estimation Modeling
• Tracking and identification of two objects. \( CM = [0.65 \ 0.35; \ 0.35 \ 0.65] \). (High confusion)

Reacts to Uncertainty

L1 Tracking


- **Wide Area Motion Imagery**
  - *Layered Sensing* – Persistence Surveillance
  - *Multisource Sensing* – Use various sensors

- **Tracking via L1 Minimization**
  - L1 – sparse representation for robustness
  - Particle Filtering – Non-Gaussian
  - eL1-PF – track /ID objects, extended target changes (Fusion10)
  - mL1-PF – track /ID objects, multiple sources (Fusion11)
  - L1-BPR – Bounded Particle Resampling (CVPR11)
  - L1-BPR+R – Bounded Particle Resample+ Registration (Fusion11)

- **APPLICATIONS – Persistent Surveillance**
  - Tracking and ID – WAMI Multiple Vehicle Tracking
  - Group Track and ID – WAMI Multiple Vehicle Group Tracking
Framework of the mL1-PF Tracker


- **Multiple Sensor Inputs** to capture
- **Particle Filtering Updates** based on sparse representation

\[ y \approx \mathbf{Ta} = a_1 \mathbf{t}_1 + a_2 \mathbf{t}_2 + \cdots + a_n \mathbf{t}_n \]

\[ y = \begin{bmatrix} y_1 \\ \vdots \\ y_M \end{bmatrix} \in \mathbb{R}^D \quad \mathbf{t}_i = \begin{bmatrix} \mathbf{t}_{i,1} \\ \vdots \\ \mathbf{t}_{i,M} \end{bmatrix} \in \mathbb{R}^D \quad \mathbf{a} = \begin{bmatrix} a_1 \\ \vdots \\ a_M \end{bmatrix} \in \mathbb{R}^n \]
Sparse Representation for Tracking


- A candidate $y$ approximately lies in a linear subspace, which is spanned by templates from past observation.

\[ y = a_1 t_1 + a_2 t_2 + \cdots + a_n t_n + \epsilon \]

- **Rewrite as**

  **Target Templates**
  \[
  y = a_1 t_1 + a_2 t_2 + \cdots + a_n t_n
  \]

  **Trivial Templates** \([I - I]\)
  \[
  e_1 i_1 + \cdots + e_d i_d + e_{-1} i_{-1} + \cdots + e_{-d} i_{-d}
  \]

- **Task:** find a **sparse** solution for \(a = [a_1, \ldots, a_n]'\) and \(e = [e_1, \ldots, e_d, e_{-1}, \ldots, e_{-d}]'\).
Why Sparse Representation


Comparing **Good** and **Bad** Candidates

Mei & Ling, ICCV’09

Good target candidate approximated by templates

Bad target candidate approximated by templates
L1 Tracking Methods


- Particle filter framework

**Algorithm 1** Particle filter for L1 tracker

1: At $t = 0$, initialize samples $x_0^i$, for $i = 1, 2, \ldots, N$
2: for $t = 1$ to number of frames do
3:   for $i = 1$ to number of samples do
4:     Draw sample $x_t^i$ with respect to $p(x_t|x_{t-1})$
5:     Prepare the observation $y_t^i$ from $x_t^i$
6:     Calculate the observation probability $p(y_t^i|x_t^i)$
7:     Resample with respect to $p(y_t^i|x_t^i)$, the number of times that $x_t^i$ appears in the new set is $N \times p(y_t^i|x_t^i)$
8:   end for
9: end for

Blasch/Seetharaman – DDDAS Review 2013
LOFT Tracker


Target / Object of Interest

Frame(t)

Region of Interest Generation (Get Next ROI)

Particle Filter Prediction

(Hypothesis Management

(Limited-) Hypothesis

Vehicle Dyn.

Target Localization

Particle Filter Update

DataFusion

Descriptor Generation

ROI Descriptor

Intensity

Contour

Texture

Object Position (t)

ProbMap

Object of Attention

Flux-based Motion Detection

MOG-based Background Subtraction

Car Detection

Building Detection

Road Detection -Image-based

GIS-based

Focus of Attention

Temporal-based

Dynamic Scene Info

Moving Objects/

Changed Regions

Object Classification-based

Static Scene Info

- Metadata (IMU)
- prior knowledge
- GIS (road maps)

KOLAM

Image and Track Visualization

Descriptors

Generation

Intensity

Contour

Texture
Compensate the camera motion through background registration

- Scale Invariant Feature Transform (SIFT)
- RANdom SAmple Consensus (RANSAC)

Unregistered (Click to play)
ISIL – ITAD WAMI Tool (2)

- Compensate the camera motion through background registration
  - Scale Invariant Feature Transform (SIFT)
  - RANSAC
  - Registered (Click to play)
L1 Video Processing


• Aerial Surveillance (Simultaneous Track and Identification)
  • Combine with other sensors (HUMINT), context (terrain) data
L1 Video Processing


- **Aerial Surveillance** *(Simultaneous Track and Identification)*
  - Combine with other sensors (HUMINT), context (terrain) data
L1 Video Processing


- **Aerial Surveillance (Simultaneous Track and Identification)**
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Cloud Enabled Robotics System


- Joint Work
- Robotics and Fusion – Target Tracking
  - Haibin Ling (Temple)
  - Dan Shen (Intelligent Fusion Technologies)
- Binghamton University – Cloud Computing
  - Yu Chen – Computer Science
  - Bingwei - PhD Student
- DDDAS processing for Fusion and Video Analysis
  - Game Theoretical Modeling and Control
  - Computational Issues for Software
- Other: Applications of DDDAS – Text Analysis
  
Multi-INT Tracking and ID


- **Current** – predefined scheme, tasks
- **New** – cloud computing has quick response, high flexibility with VMs
  - Hadoop MapReduce scheduler

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Testbed Evaluation


• Experimental prototype
  – A cloud-enabled distributed robotic network
  – A UAV drone tracking three mobile robots
  – A cloud testbed in our datacenter
A Cloud-enabled Robotic System


- Faster robotic applications development
- Easier to get started
- More efficient robot resources usage
A Robot Network

Robot Operating System (ROS)
- The cloud communicates with ROS directly
- Each robot team must have at least one ROS master

Running modes
- Local mode
  - A manager node will be chosen and host the ROS master
- Cloud mode
  - Communication delays

Architecture

- Application layer
  - Management APPs vs. Services APPS vs. User APPs
- The middleware layer
  - The Application Programming Interface (API)
- The platform layer
  - Computing, storage and databases, Robot Operating System

Workflow

Cloud testbed

- 16 servers in our data center
- Each server: two Intel Xeon E5405 Quad-core processors at 2.0GHz, 32GB memory, and 3TB storage
- Xen Cloud Platform (XCP) 1.6
- Management software Citrix XenCenter

Experiments
AR Drone 2.0 --- Change the direction of the HD camera

Change the wireless setting of the drone
- By default, the drone will create an access point and let devices connect to it:
- Login using telnet and disable the default ad hoc wireless and connect drone to a wireless router as same the robots
- “iwconfig ath0 mode managed essid Netgear; ifconfig ath0 192.168.1.20 netmask 255.255.255.0 up; route add default gw 192.168.1.1”
Hardware-Software System Integration

Flow chart of the control system

Main Thread
- Capture an image from the drone
  - Conduct visual tracking
  - Call PE game to calculate the robot controls

SetTimer 1 for robot control (period 0.5s)
SetTimer 2 for drone (period 0.1s)

Response to user inputs

OneTimer 1 (robots)
- Send the calculated to robots
  - Capture an image from the drone
  - Conduct visual tracking
  - Estimate one step ahead states of the robots based on the current stats and the controls
  - Call PE game to calculate the robot controls

OneTimer 2 (drone)
- Take a photo for the facing down HD camera
  - Get the location of the marks on floor
  - PID controller to follow a reference location
  - Send controls to drone
Top-view Tracking Preliminary Result

- One newly captured sequence
- Four trackers tested
Tracking of Robots

AR Drone

Feature extraction

Reprojected

Top view

Local view
Top-view Tracking Preliminary Result

- On a Intel Core i5 3.46GHz CPU with 8GB memory, the algorithm can process 6.3 frames per second
- More results are available at http://www.dabi.temple.edu/~hbling/Projects/soa2/topview-20130415.zip
Experiments

- Hover
- Follow
Experiments

- Dynamic Follow
Comparison of image processing performance

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  Erik Blasch

• Multimodal Imagery Sensing
  • 3D Challenges
  • Persistent Appearance models
  • Bundle adjustment
  Guna Seetharaman