GPU-Accelerated AI Applications for Smart Civil Infrastructure

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Infrastructure Industry Going Digital

Planning | Design | Construction | Operations

Digital Context

2017 Industry Reports
www.arcweb.com

Engineering Design Tools for Plant, Infrastructure, and Building Modeling 2017

GIS 2017

Asset Reliability Software and Services 2017

ARC Advisory Group

Constant Currency ARR

7.5% Average Annual Growth Rate

2013 2014 2015 2016 2017
Bentley Software Platform Technology

ProjectWise
- Project management

MicroStation
- Modeling Platform

AssetWise
- Asset management
Infrastructure digital Twin (iTwin)

Data

Physical asset

Intelligence

Digital twin

Actions
Semantic 3D City Model
Applied Research for Infrastructure Digital Twin

- Sensing Inspection
- Data Acquisition
- Data Analysis
- System Modeling
- Decision Support

Physical asset     Digital twin
AI Application Research

- Machine Learning
- Expert Systems
- Artificial Intelligence
- Robotics
- Language Processing
- Computer Vision
- Search & Optimization


- Evolutionary Deep Learning (eDL) Framework

Deep Neural Network:

- Input Layer
- Hidden Layer
- Output Layer

Deep Learning Evolutionary Framework

- Problem Definition
- Run Optimization
- Options

- Decision Variable File
- Configuration
- Output Directory

- Number of Decision Variables: 2
- Number of possible solutions: 25,001
- Number of Objectives: 1

- Evolutionary Algorithm
- Deep Learning Architecture
- Optimization Techniques

- Bentley Systems, Incorporated
- © 2016
GPU-Accelerated Analysis

Water Quality Analysis

Read Hydraulics at step t
Write to GPU
Water Quality Analysis
Read from GPU
Write Results
GPU-Data-Driven Model

- Big data, big opportunity
- Data ≠ information
- Capture data relationships
- Fast ANN model training/calibration

On CPU

On GPU
GPU-Pump Scheduling

- Optimize pump operation
- Minimize energy cost
GPU-Accelerated Pump Scheduling

- Daily Pumping Energy Cost Saving (%)
- Current Operation: Optimized with Hydraulic Model, Optimized with ANN Model
- Computation Time (minutes): 3000, 2000, 1000, 0
- Speed up: Hydraulic model, ANN Model
- Fitness: Trained ANN Response
- Graphics User Interface
  - Deck
  - Fitness
  - Solution
  - Trained AI Response
  - Model and Geospatial Database
Singapore Smart Water Grid (SWG)

- 700 plus sensors
  - Pressure
  - Flow
  - pH, ORP, conductivity, temperature and turbidity
Real Time Monitoring for SWG: Digital Twin for Water Systems

• Challenges
  – Interoperability for sensors, communication and data management
  – Data analytics
  – Job redesign for PUB staff
  – Public communication
  – Further research and testing for SWG technology
Operation Analytics

• Predictive analytics
• Anomaly detection
Case Study

• System layout with sensor locations
• One inflow time series in 5-min interval
• Pressures in 15-min interval at 8 locations
• Service tank levels in 15-min interval
• Hydraulic model
Data Analysis and Event Detection

Flow Data Preprocess

Before pre-processing

After pre-processing
Pressure Data Preprocess (Stn11)
Anomaly Event Detection

Event detected on 9/23/17
Event detected on 9/26/17
700mm pipe break on 9/26/17
Simulation Results

Event on Sept. 23 2017

Increased flows

Event on Sept. 26 2017

Pressure drops
Anomaly/Leakage Event Localization

- Model-localized hotspots at 11:15 PM on Sept. 23 2017

PUB Field Record

<table>
<thead>
<tr>
<th>Date</th>
<th>Location</th>
<th>Description</th>
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<tbody>
<tr>
<td>Sept. 26</td>
<td>Bukit Batok W. Ave 6, Hdb-bukit Batok, 650185</td>
<td>700mm mains longitudinal crack</td>
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</table>
Digital Twin for Engineering Structures

Sensor placement
Vision sensor

SHM Pretest

Data analysis & information extraction

FE Model calibration
Damage detection
Load identification

SHM Extractor

SHM Calibrator

Assessment, rating & maintenance

- 0
- 0.05
- 0.1
- 0.15
- 0.2
- 0.25
- 0.3
- 0.35

- 1
- 5
- 10
- 15

Time (S)

- 0.05
- 0.05

in/s

0
100
150

- 0.85
- 5Dme(S)100

- 1.0
- 1.0
- 1.0
- 1.0

- 1
Applied AI Research for Infrastructure Digital Twin

**Sensing Inspection**

**Data Acquisition**

- DarwinSHM Pretest for SHM Sensor placement
  - Accelerometers
  - Strain Gauges


Applied AI Research for Infrastructure Digital Twin

- Sensing Inspection
- Data Acquisition
- Data Analysis
- System Modeling

- Integrated with STAAD
- Responses
  - Displacements & Strains
  - Frequency & mode shapes
- Parameters
  - Section area
  - Young’s modulus
- Features
  - FE model calibration
  - Damage detection
  - Load identification
Finite Element Model Calibration

• Update finite element model for in-service structure

• Research projects
  – Applied to buildings and bridges
Building Finite Model Calibration

- UCLA Factor Building
- Sensor data
- Modal Shapes
- Frequency

<table>
<thead>
<tr>
<th>Mode</th>
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<td>3</td>
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<td>0.576</td>
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<td>0.795</td>
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<tr>
<td>8</td>
<td>2.774</td>
</tr>
<tr>
<td>9</td>
<td>4.151</td>
</tr>
</tbody>
</table>
Indian River Inlet Bridge Location

- Bridge FE model calibration (with Dr. Shenton from Uni. Delaware)
New Indian River Inlet Bridge
Sensor Layout Layout

- 69 strain and temperature sensors
- 9 tiltmeters
- 16 chloride sensors
- 27 accelerometers
- 3 displacement gauges
- 2 anemometers
Sensor Placement: Indian River Inlet Bridge in Delaware

40-strain gauge

Maximum coverage ratio

Coverage ratio

Instrumented

Optimized
Bentley Darwin Optimization

• Tool for calibrating a model of a structural system using measured structural response data

• UD expertise
  – Bridge engineering
  – Structural Health Monitoring
  – Indian River Inlet Bridge

• Test the tool by calibrating a signature bridge using strain response data
Strain Response Used for Calibration

- Load Test 2, November 2012
- 4 – truck pass
  - 110 strain response values
  - Magnitudes range from 2.5 to 90 microstrain
Calibrated Strain Response
Validation of Calibrated Model

• 6-truck pass used for validation
Structural Health Monitoring and Advanced Analysis of Bridges: A Pathway to Improved Performance

University of Delaware Center for Innovative Bridge Engineering

Rate

Maintain

Sense

Calibrate

Bridge Digital Twin
Video Camera as Sensor

• Conventional Sensors
  – Placed on structure
  – Limitations: high cost, safety concerns, service interruption

• Vision-based sensors
  – Remote sensing (non-contact)
  – Cost effective
Vision Sensor (Video Camera) for SHM
DRBA Bridges Test

- 28 strain gauges, 8 accelerometers, 6 displacement sensors and 2 tiltmeters (UD)
- Two video cameras (Bentley)
- Measuring responses for 5 cuts
Video Analysis for Extracting Structural Responses

Convention factor: 0.3137 inch/pixel
Comparison: Displacement at T10

![Graph showing comparison of displacements at T10 with sensor and video adjustments.](image-url)

- Cut 5 Displacements: S1 (T11(T6)/T10)
  - T11(T6) shifted -0.0143 in
  - Sensor T10-adjusted
  - Video - Phase-based-adjusted
Comparison: Displacement at T11

Displacement (inch)

Cut No.

Sensor T11- adjusted

Video-phase based at T11-adjusted
Infrastructure Inspection with Machine Learning
Deep Learning Approach for Defect Detection

Image Acquisition

Model Training

Defect Detection & Segmentation

Defect Evaluation with 3D Model

Deep Learning

- Obtain inspection images and videos
- Work with Bentley users
- Label images with defects (e.g. cracks and corrosions)
- Train models e.g. Faster RCNN and/or Mask RCNN
- Model inference on images and videos
- Applications of various cases (buildings, bridges, roads and tunnels)
- Build 3D model with inferred images
- Perform defect statistics
  - Crack length, width and area
  - Level of corrosion and areas
Deep Learning Model for Crack Detection
Deep Learning Applications – Crack Detection

Bridge with Deep Learning (Australia)

Road Inspection (Macao China)
Crack Detection and Evaluation with 3D Model:

![Crack Detection and Evaluation with 3D Model](image-url)
Corrosion Detection and Segmentation

- Applied semantic CNN (DeepLab) for corrosion detection and segmentation
- Classified by Corrosion Index (CI): Heavy: \(0.75 < CI \leq 1\); Medium: \(0.6 < CI \leq 0.75\); Light: \(0 \leq CI \leq 0.6\)
Soft-Story Building Detection for Seismic Retrofit

• What is a soft story
  – level less than 70% as stiff as the floor immediately above it

• Characteristics of soft story buildings
  – multi-story building with Wide opening
  – Multi-use buildings with commercial retail on the ground floor
  – Retail buildings with mostly glass front

Examples of typical soft-story buildings
Soft-Story Risk

• About 50% damaged homes at CA earthquake in 1989 were soft-story

• 1994 Northridge earthquake CA
  – about 200 buildings seriously damaged or destroyed
  – 16 people died at Northridge Meadows soft story apartment complex

• Need for retrofitting soft story
Soft-story Buildings Classification

• Buildings classified by engineers
  – Accurate but time consuming
  – Good dataset for training deep learning models

• Apply deep learning
  – Images from Google Street View
  – Training data from Los Angeles
  – Testing data from Santa Monica

Soft-story buildings map. Classified by engineers at Santa Monica, CA

A typical soft-story building from google street view using Santa Monica DS
Proposed Approach

1. Extract images for engineer-classified SS buildings
2. Label images for training DL models
3. Train DL models
4. Test DL on new images
5. Evaluate results
6. Add true positive SS images to training dataset
Dataset

• Training
  – 1267 Buildings classified by engineers
  – non-soft story buildings

• Testing
  – 1500 building from Santa Monica
  – non-soft story buildings
Soft-story Detection

• Data sets preparation
  – Only using images of buildings with clear opening of the first floor (900 images)
  – Annotate only part of the building that may cause collapse.

• Training
  – Use 800 images for training and 100 images for testing
  – Using feature extractor network with the best accuracy, ResNet101 & Inception-ResNet
SS Detection Model Performance

- Tested 2399 images
- 75% detected with confidence >75%

Confidence levels:
- 0-25%: 80 images
- 26-50%: 186 images
- 51-75%: 353 images
- 76-90%: 401 images
- 91-96%: 404 images
- 97-99%: 975 images
Integrated Work Flow for Soft Story Detection

1. Obtain List of Address
2. Download Images from Google Street View
3. Run Inception-ResNet for Soft-Story Detection
4. Annotate SS in Google Map

<table>
<thead>
<tr>
<th>Address</th>
<th>City</th>
<th>State</th>
<th>Zip</th>
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<tbody>
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<td>5802 4TH AVE NW</td>
<td>SEATTLE</td>
<td>WA</td>
<td>98107-2117</td>
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<td>5806 4TH AVE NW</td>
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<td>WA</td>
<td>98107-2138</td>
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</table>
Test Area: San Bruno, CA

- Acquired and tested ~7600 addresses.
- ~3400 addresses were detected as soft-story.
SS Buildings Annotated in Google Map (San Bruno, CA)
Test Area: Seattle, WA

- Acquired and tested ~8200 addresses.
- ~2700 addresses were detected as soft-story.
SS Buildings Annotated in Google Map (Seattle, WA)
Research Collaborations

- Multidiscipline: Civil/Environmental/structural, Electrical Eng., Computer science etc.
- Multi Sectors: Water, power, transportation and buildings etc.
Summary

• Research for AI-based systematic approaches
• Connect data environment with Bentley software
• Construct various digital models
  – Semantic models: 3D mesh/texture models, point cloud etc.
  – Data-driven: machine learning, statistics etc.
  – Physics-based: finite element analysis, hydraulics and water quality etc.
  – Decision-support: optimization models
• Enable digital twin for smart infrastructure
• Accelerate computations
Thank You!

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