Using Deep Learning for Tropical Cyclone Intensity Estimation

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1. Motivation
2. Overview of current techniques
3. Data/Methodology
4. Results
5. Applications
6. Implications/future work
Motivation

- In situ observations from aircraft are not always available
- Tropical cyclone (TC) warning centers use different variants of satellite-based methods
- 10-20% uncertainty in post analyses when only satellite based estimates are available.
- Can deep learning be used to objectively and
Dvorak Technique

  - Uses enhanced IR and/or visible satellite imagery
  - Very subjective
  - Dependent on user expertise
- Objective Dvorak technique [1998]
  - Computer based algorithms to recognize patterns
  - Location of the eye must be identified by an expert
- Advanced Dvorak technique [2007]
  - Introduces regression equations

Current Methods

- Subjective
- Don’t generalize well
- Inconsistent
- Dependent on user expertise

Deep Learning

- Objective
- Generalize well
- No need for user expertise
- Large amounts of training data
Data

- US Naval Research Laboratory (NRL)
  - 2000 to 2016
  - ~30 minute interval
  - Pacific and Atlantic
  - Multiple geostationary satellites
    - GOES, Himawari, MTSAT, etc...
  - ~45,000 images

Source: https://www.nrlmry.navy.mil/tcdat/tc05/ATL/12L.KATRINA/ir/geo/1km/
Truth data

• Best tracks (HURDAT, HURDAT2)
  • Post-storm analysis of intensity, central pressure, location and size
  • 6 hour intervals
• Specially subsetted portion of the HURDAT2 dataset [Landsea and Franklin 2013]
  • Restricted to time periods that had airborne recon data
  • One hour intervals

Source: Atlantic Hurricane Database Uncertainty and Presentation of a New Database Format, Landsea, C.W. and J.L. Franklin, Monthly Weather Review 2013 141:10, 3576-3592
Methodology

- Classes based on maximum sustained wind speed
  - 5 kts intervals
- Remove images where more than 20% of the pixels are black
- Split data into train/test/validation sets
- Augment images before training
  - Rotate, zoom

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Architecture and Training

• Caffe reference network (CaffeNet)
  • Transfer learning
    • Trained on ImageNet
  • 5 convolutional layers
  • 3 fully connected layers
• Caffe
• NVIDIA Tesla P100
• ~90% validation accuracy

Adapted from: Hu et al. 2015 Transferring Deep Convolutional Neural Networks for the Scene Classification of High-Resolution Remote Sensing Imagery. Remote Sensing, 7(11)
Preliminary Results

- Our model
  - Top-1 accuracy: **86.4%**
  - Achieved RMSE of **10.00 kt**
- Atlantic and Pacific
  - North Atlantic
    - Piñeros et al. (2011): **14.7 kt**
    - Ritchie et al. (2012): **12.9 kt**
  - North Pacific
    - Ritchie et al. (2014): **14.3 kt**

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Activations

Input Image

Conv1 Activations
Ongoing Research

• Training a network where storms are unique to test/training set
• Include data from other sources
  • Microwave imagery
• Evaluate performance with different network architectures
  • Modality Hallucination
Intensity Estimation Service

• Develop a near real-time tropical cyclone intensity estimation service
  • Monitor NHC invest areas
  • Download images from invest area
  • Predict intensity (wind speed)
  • Store estimations in DB
  • Information can be retrieved through API

• Work with endusers to develop a website that will display past and present storm information along with estimated wind speed information and relevant overlays

• Utilize standards-based services (WFS, SOS, WCS, WMS, GeoJSON)
  • integration with AWIPS/N-AWIPS
Key Take Aways

• Deep learning can be used as a tool for TC intensity estimation
  • 86.4% top-1 accuracy
    • Performance should increase with more training data
  • Network appears to utilize storm shape and patterns, similar to current operational techniques
• Build a web-service to distribute storm data in near real time
• Dan Cecil (NASA MSFC)
• Derrick Herndon (CIMSS UW-Madison)
Thank you

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