Traveling Ionospheric Disturbances detection with Convolutional Neural Networks: a proof-of-concept with the 2012 Hawaii earthquake and tsunami

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Motivation

Detection of Tsunami Events

- Tsunamis can trigger internal gravity waves (IGWs) that cause perturbations in the natural Total Electron Content (TEC) in the ionosphere
  - Known as Traveling Ionospheric Disturbances (TIDs)

- Can be detected through Global Navigation Satellite Systems (GNSS)

- Scalable systems for TID detection will allow improvements to current tsunami detection systems

Figure: Graphic showing how GPS/GNSS satellites can detect IGWs from Tsunamis. Taken from "Ionospheric GNSS Total Electron Content for Tsunami Warning", Liu et. al., 2019.
Motivation

Building On Existing Work

- Analyzed the TIDs induced by the tsunamis off the coast of Hawaii generated from **2012 Haida – Gwaii Earthquake**

- Utilized an existing slant Total Electron Content (sTEC) estimation approach (VARION), “Real-Time Detection of Tsunami Ionospheric Disturbances with a Stand-Alone GNSS Receiver: A Preliminary Feasibility Demonstration” (Savastano et. al., 2017).

- **G10 satellite shows TID ~8 minutes prior to a tsunami making landfall in the Hawaiian islands.**
  - Opportunity for detection

- Data is abundant and readily available
  - ~ 9 TB of GNSS data from 1992 to present day
  - can be leveraged by machine and deep learning approaches

![Figure: Graphic showing the Tsunami waves as well as the TEC variation measurements of the satellites right before the tsunami made landfall. Taken from “Real-Time Detection of Tsunami Ionospheric Disturbances with a Stand-Alone GNSS Receiver: A Preliminary Feasibility Demonstration” (Savastano et. al., 2017).]
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**Figure:** sTEC variations for two hours (08:00 to 10:00 UT – 28 October 2012) vs. distance from the Haida Gwaii earthquake epicenter. The TIDs are clearly visible in the interval of significant sTEC variations (from positive to negative values and vice-versa). The vertical and horizontal black lines represent the time (when the tsunami arrived at the Hawaiian Islands) and the distance (between the epicenter and the Big Island), respectively; it is evident that G10 detected TIDs before the tsunami arrived at Hawaiian Hawaii Island. Taken from, “Real-Time Detection of Tsunami Ionospheric Disturbances with a Stand-Alone GNSS Receiver: A Preliminary Feasibility Demonstration” (Savastano et. Al., 2017)
Motivation
Deep Neural Networks

• Shown to be highly effective on time-series anomaly detection tasks
  • “Detecting Spacecraft Anomalies Using LSTMs and Nonparametric Dynamic Thresholding” (Hundman et. al. 2018)
  • Works well with large amounts of datasets

• Can aid in providing start and end times (a sequence of observations in time)
  • Bound TID detections with estimated times

• Can be used in conjunction with current TID detection methods
  • Help augment current tsunami detection systems

• Current deep learning methods using recurrent neural networks (RNNs) cannot handle the non-continuity of the data
Encoding Time-Series as Images
Gramian Angular Fields

- Leveraged Gramian Angular Fields (GAFs) encoding, “Imaging Time-Series to Improve Classification and Imputation” (Wang et. al., 2015).
  - **Encodes temporal information as image**
  - Preserves temporal dependence → time step increases as position moves from top-left to bottom-right in the GAF

- Other work has leveraged GAFs for time-series anomaly detection with deep learning.

- There are distinct (visually interpretable) differences in the images between classes.
  - Star patterns occur where the perturbations exist

- Utilized a window size of 60 (minutes) for these experiments.
  - Sufficiently covers TID perturbations with this data

**Figure:** Process of how Gramian Angular Fields are encoded from a time series (Imaging Time-Series to Improve Classification and Imputation, Wang et. al., 2015)
Encoding Time-Series as Images

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![Figure](top) A representation of how time series windows are converted into Gramian Angular Fields (GAFs) with the TEC data gained from one ground station and satellite
Encoding Time Series as Images

Example Encodings

Image encoding from an anomalous event

Image encoding from a normal event
Encoding Time Series as Images

Example Encodings

Image encodings from an anomalous event

Image encodings from a normal event
The Training Pipeline

Summary of Process

Training Data
- TEC data from TIDs

Encoding using the GAF Method

Model Architecture and Hyperparameters

Train Model

Unseen TEC data

Encoding using the GAF Method

Trained Model

Output Predictions

Convolutional Neural Network (CNN), ResNet34
Out-of-sample (OOS) Experiments
Simulating Real-Time

- Used 30 out-of-sample (never seen by model) streams of images to validate model performance.
- Predicted the class of images (chronologically)
  - prediction used to indicate start and end times for TID detection
- Variability in the end-time due to approximation (30 minutes after start)
  - future work should improve labeling process
- Most false positives are short-length sequences (e.g. a few minutes or less)
  - could subsequently filter with simple rule-based methods
  - could improve system performance

**Figure:** Some of the predictions that were generated from our trained model. The top graph is the TEC values with the TID times bounded. The two graphs on the bottom show the prediction value and the confidence of the prediction.
Out-of-sample (OOS) Experiments

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Validation (OOS)

Recall: 100%
Precision: 85.7%
F-Score: 92.3%

Figure: A distribution of the length of the sequence types that we were able to predict
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Neural Network Architecture

Convolutional Neural Networks

Figure: A graphical representation of the general Convolutional Neural Network (Object Recognition with Gradient Based Learning, LeCun et. al., 1989)
Neural Network Architecture

ResNet

Figure: A graphical representation of learning block within a residual network (Deep Residual Learning for Image Recognition, He et al., 2015)
Encoding Time Series Images

Specifics of the Encoding

- Requires normalizing the sequence of time series data either to the range of \([-1, 1]\) or \([0, 1]\)
- Converting the normalized data points into polar coordinates
- Using the angular component of each polar coordinate, construct a matrix by calculating a trigonometric sum or difference between every possible pair of points in the sequence

Figure: Process of how Gramian Angular Fields are encoded from a time series (Imaging Time-Series to Improve Classification and Imputation, Wang et. al., 2015)