Big Data and Real Time Analytics: Use of a Hierarchical Temporal Memory Continuous Learning Algorithm for Fire State Determination

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Outline

• Introduction
  • Concept of Fire State Determination
  • Drivers
  • Sensors and sources of data

• Research
  • Experiments
  • Algorithm development
    • Simple, rate of change - threshold
    • Hierarchical Temporal Memory

• Next Steps
Prior Work and Background

• Fire environment classification
  • Temperature
  • Heat flux
  • HRR
  • Products of Combustion
    • CO and other combustion gasses
    • Smoke

• Multi-sensor detection criteria & algorithms
  • Combination CO & smoke detectors
  • Geared towards nuisance reduction

• Non-Traditional Fire Sensors
  • Minimal published work
Prior Work and Background

• Multi year project examining building sensors for fire detection and information on the fire state
• Confirmed that many existing building sensors can be leveraged for this use
• Patented and patent pending system and methods for detecting and classifying fires based on “non-fire” sensors
• Still a need to be able to perform the necessary analysis in “real-time” to make it useful, thus this work
Fire Detection

• How do we typically detect fires?
  • Observation (i.e. sight, smell, etc.)
  • A sensor or system detects and informs us
    • Smoke detector
    • Heat detector
    • Flame detector
    • Gaseous detector
    • Flow switch
    • Etc.

• What do we typically learn from the detection of a fire?
  • Whether there is a fire or not (or at least whether the system believes one to exist)
Purpose of Fire Detection Systems

**Current**
- Intended to provide sufficient notification to occupants to facilitate safe egress
- To reduce costs associated with losses
- Perceived as expensive, primarily point source

**Ideal**
- Provide real-time information to stakeholders to better inform decisions
- Reduce costs, injuries, and lives lost via rapid detection and continuous monitoring
- Capitalize on “low-cost” sensing technologies

Limitation is regulatory (i.e. spacing), technology (point source), and cost (decreasing benefit)
Definition: Fire State Determination (FSD)

• Rather than provide a simple binary signal sensor data is used to inform about the state the fire is in (i.e. growing, decaying, spreading, etc.)

• Provides quantitative information or at least a scale

• Objective is to show how the temporal and spatial conditions are changing so that informed decisions can be made
FSD: Fire Growth & Prediction
Real Time Data Analysis

• Real time data analysis and decision making already integrated into building systems and currently being used

• Energy efficiency and occupant comfort primary drivers

• Limited detailed information available for fire
Example: Real Time Lighting Energy Mapping
Sensors

- Environmental/comfort sensors used to control temperature, humidity, lighting, air quality
- Security sensors used to detect movement via various sensing technologies
- Standard “fire” sensors also included

Extend the use of these sensors for fire detection and prediction and unify with fire system
Objective of Research

- To define and characterize the fire environment using a range of sensor technologies;
- To determine how and whether the signals from a fire can be suitably differentiated from background and nuisance sources;
- To determine what signals may be most relevant at different stages of fire growth, fire monitoring and prediction;
- Long term: to transmit information to EFR’s via network prior to even leaving station, continuously update information
Prior Experiments

• Small-scale (8’ x 8’ x 8’ room)
  • Pan heptane fires 3-35 kW
  • Fire growth: slow, medium, fast, ultrafast fire growth curves using propane and methane burners to a maximum of 150 kW

• Large-scale
  • Furnished living room in house

Tests at all scales showed ability to detect, measure, and monitor the changing conditions in the space and the fire state. Analysis done post-fire.
Small-Scale

Slow Growth

Fast Growth
Large Scale Testing

• Full room furniture tests
Large Scale Results
Data Analysis – The 5 V’s

• **Volume**: This dimension refers to the amount of data
• **Velocity**: This refers to the rate at which data is being generated
• **Variety**: This dimension tackles the fact that the data can be unstructured
• **Veracity**: This is all about validity and the correctness of data
• **Value**: As the name suggests, this is the value the data actually holds
Data Ecosystem

• Storing data
• Processing and enriching data
• Data analysis and visualization/presentation

• For fire applications it is “easy” to analyze data after the fact and make conclusions, however in real-time it can be challenging.
Challenges and Approach

• What defines a fire and how to recognize it with data?
• What nuisance sources are there that may create similar data signals?
• What if baseline conditions change in the monitored space?

• Train system on what a fire “looks” like using data (i.e. know in advance what it looks like)
  • Fire may not “look” the same based on type/size/location of fire
• Allow system to learn based on data fed to it (unsupervised learning)
  • We may not be able to define why a fire is a “fire”
Hierarchical Temporal Memory (HTM)

- Continuous learning algorithm that is constantly being trained on the data it is receiving and does not require an entire data set for training
- Models temporal and spatial patterns in real-time.
- Based on modeling of the neocortex which assumes that decisions/learning are based on memory and the recall of sequences of patterns
- Conceptually ideal for streaming data sets which may change over time
- Compare observed data to the predicted value to produce an anomaly score (not just useful for fire)

HTM is Dynamic – It Doesn’t Decide in Advance What A Node Should Learn
Hierarchical Temporal Memory (HTM)

HTM Primary Functional Steps

• The core HTM algorithm receives a stream of inputs, $x_t$, which are then transformed using an encoder and spatial pooling process to create a sparse binary representation of the input data, $a(x_t)$. The algorithm initiates a raw anomaly score that is then transformed into an anomaly likelihood.

• An advantage of a continuous learning system, is that a shift in the system behavior will result in a high anomaly score initially, but the anomaly score will reduce over time as the model learns what the new "normal" conditions are.
HTM Learning

Shift in underlying data. Initial spike is anomalous but subsequent data is not.
HTM Results Small-Scale Fire

• Temperature, RH, Light signals shown from an off-the-shelf “comfort” sensor
• Streamed data from sensors into HTM algorithm in real-time
• Plotted Anomaly Likelihood for each sensor individually
• Ignition occurs at 0 s
HTM Results

• Anomaly detection can be based on single sensor or combined
• When combined can set a “threshold” value, anything less is not deemed anomalous
HTM Results

• First anomaly for each observed parameter noted with a diamond
• Temporal relations are important
• Not all sensors may show an anomaly
Alarm Time Comparison

• While most spaces won’t have a smoke detector or heat detector in every room, comparisons were provided for numerous tests.
• The sensor suite responded in a similar time frame as a heat detector but significantly slower than a smoke detector centered in the room on the ceiling.

<table>
<thead>
<tr>
<th>Detector</th>
<th>HTM System</th>
<th>Smoke Detector</th>
<th>Heat Detector</th>
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</thead>
<tbody>
<tr>
<td>Wall Sensor Suite</td>
<td>360</td>
<td>90</td>
<td>330</td>
</tr>
<tr>
<td>Ceiling Sensor Suite</td>
<td>368</td>
<td>90</td>
<td>330</td>
</tr>
</tbody>
</table>
Conclusions

• Very low rate of false positives and relatively low rate of false negatives observed in baseline HTM approach

• HTM algorithm had no specific domain expertise in detecting the fire state, and was still able to detect anomalies in the sensor data from the fire tests

• Improvements to HTM algorithm (windowing, weighting factors, etc.) expected to improve results

• Data stream able to provide actionable information on the Fire State in addition to anomaly detection
Next Steps

• Testing for generation of additional data sets (fire and non-fire)
  • Extensive background data sets being generated presently
  • Real-time IOT feedback
  • Multiple locations
  • Multiple parameters

• Synthetic data generation (i.e. CFD of virtual fires to populate data sets)
• Continued refinement of HTM algorithm
Questions?