Automated Wildfire Detection Through Artificial Neural Networks

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Wildfires have a profound impact upon the biosphere and our society in general. They cause loss of life, lead to the destruction of personal property and natural resources, and alter the chemistry of the atmosphere. In response to the concern over the consequences of wildland fire and to support the fire management community, the National Oceanic and Atmospheric Administration (NOAA), National Environmental Satellite, Data and Information Service (NESDIS) located in Camp Springs, Maryland gradually developed an operational system for the routine monitoring of wildland fire through satellite observations. The Hazard Mapping System (HMS), as it is known today, allows a team of trained fire analysts to examine and integrate, on a daily basis, remote sensing data from Geostationary Operational Environmental Satellite (GOES), Advanced Very High Resolution Radiometer (AVHRR) and Moderate Resolution Imaging Spectroradiometer (MODIS) satellite sensors, from which the HMS fire analysts generate a 24-hour fire product for the conterminous United States. Although assisted by automated fire detection algorithms, NOAA has not been able to eliminate the human element from their fire detection procedures. As a consequence, the manually intensive effort inherent to HMS has prevented NOAA from transitioning to a global fire product as urged particularly by climate modelers. NASA, at Goddard Space Flight Center in Greenbelt, Maryland, is helping NOAA more fully automate the Hazard Mapping System by training neural networks to mimic the decision-making process of the fire analyst team as well as to reproduce the automated fire-detection algorithms.

NASA's Computing, Information and Communications Technology (CICT) Program, managed out of the Ames Research Center in Moffett Field, California, provided funding for the research effort to get underway. A team of government and University personnel were assembled with the intent of applying artificial intelligence techniques to NOAA's automation problem. NASA began archiving satellite imagery from GOES, AVHRR, and MODIS satellite sensors in the summer of 2003. Three spectral channels for each of 3 science instruments were provided by NOAA NESDIS by uploading to a NASA computer within the Information Systems Division at Goddard Space Flight Center. The following spectral bands, being only a subset of those available from each instrument, were found to be the most useful in fire identification by NESDIS: MODIS channels 1 (0.66 μm), 2 (0.86 μm), 22 (3.96 μm); AVHRR channels 1 (0.66 μm), 2 (0.91 μm), 3b(3.7 μm); and GOES channels 1 (0.62 μm), 2 (3.9 μm), 4 (10.7 μm). Both reflectance and brightness temperature values were normalized by NESDIS to a range of 0 – 255.

Significant discussion, research, time, and attention went into the composition of adequate neural network training sets. Early attempts included time and geographic location parameters in addition to spectral information, but due to subsequent difficulties in obtaining convergence, ultimately only the spectral information was used. The original guiding principle in training set composition was to use NOAA's ASCII data-formatted fire product, which identifies hotspots by geographic coordinates, to locate fires within satellite imagery, and then to extract 3-band pixel information at these fire points. A subset of a typical daily HMS fire product is illustrated in Table 1.

Table 1. ASCII Data Format of NOAA Fire Product (as of 05/16/03)

Lon	Lat	Time	Satellite	Method of Detect
-80.597	22.932	1830	MODIS AQUA	MODIS
-79.648	34.913	1829	MODIS	ANALYSIS
-81.048	33.195	1829	MODIS	ANALYSIS
-83.037	36.219	1829	MODIS	ANALYSIS
-83.037	36.219	1829	MODIS	ANALYSIS
-85.767	49.517	1805	AVHRR NOAA-16	FIMMA
-84.465	48.926	2130	GOES-WEST	ABBA
-84.481	48.888	2230	GOES-WEST	ABBA
-84.521	48.864	2030	GOES-WEST	ABBA
-84.557	48.891	1835	MODIS AQUA	MODIS
-84.561	48.881	1655	MODIS TERRA	MODIS
-84.561	48.881	1835	MODIS AQUA	MODIS
-89.433	36.827	1700	MODIS TERRA	MODIS
-89.750	36.198	1845	GOES	ANALYSIS

Using a software package called Environment for Visualizing Images (ENVI), geographic coordinates were converted to pixel row and column coordinates for a particular image being processed through a series of ENVI function calls embedded in IDL code. When examining fires using ENVI in visual mode, difficulties were encountered. In particular, it was found that fires were not in the precise location where the geographic coordinates in the HMS product placed them, being offset by as much as several pixels from their expected location. Considering the 1-kilometer spatial resolution of MODIS and AVHRR, the offset error might have been 2 or 3 kilometers, but for GOES data in the thermal band (4 km resolution) the error could have been as much as 12 kilometers. This offset was attributed to 3 sources: spacecraft navigation errors, the inherent tolerances within NOAA software, and operational errors in the point-and-click method of a Fire Analyst identifying fire locations with a mouse.

One of the best clues for identifying wildfires that NOAA Fire Analysts employ is to visually inspect the 4-micron band for dark spots within NESDIS post-processed satellite imagery. NOAA software has been written in such a way that brightness temperatures assume the lowest intensity values for the hottest fires (as a means of highlighting them). In order to extract fire signatures from satellite imagery, our software performed a local minima search for the hottest pixels using the approximate location specified by the ASCII data fire product, and then collected spectral information in an area around that image coordinate in all 3 bands. Three different methods to characterize a fire across 3 spectral bands were investigated: (1) as a single pixel at an instantaneous point of time; (2) as a pixel time series demonstrating the time evolution of a fire throughout the day; and (3) as a pixel array at an instantaneous point in time. The first two techniques had mixed results in achieving neural network convergence, and were eventually discarded. However the third approach, a spatial technique consisting of 7x7 pixel arrays with the hottest part of the fire as the central pixel, was successful.

Three spectral bands of 7x7 pixel arrays, formatted as 147-element vectors, determined the number of neural network input nodes, while the number of hidden nodes in the network was initially determined by the following rule-of-thumb: start with the square root of the sum of the inputs and outputs (*i.e.*, 12). Nevertheless, even after a fair amount of experimentation, the final number of hidden nodes in our trained neural network did not vary much from the initial rule-of-thumb value. Note that only a single output node value was required to discriminate between the 2 classes – fire (1) or no fire (0). The resulting 147-10-1 feedforward backpropagation neural network was then used for training and testing. Separate, identical networks were created for each sensor. Hyperbolic tangent transfer functions were selected for all active nodes.

We experimented with three neural network packages: Java Object Oriented Neural Engine (JOONE), Stuttgart Neural Network Simulator (SNNS), and MATLAB Neural Network Toolbox. The first two tools are freely downloadable from the Internet (see http://www.jooneworld.com and http://www-ra.informatik.uni-tuebingen.de/SNNS, respectively). We found the JOONE package the most difficult to work with, though our results were similar across all three packages. The SNNS package was exceedingly useful – it was straightforward to implement, to train, and to use. As an added bonus, the final trained SNNS neural network model (*i.e.,* hidden and output node values, including node weights and activation function) is exportable as C code. As such, the neural model is directly importable to any other software architecture for data pipeline processing, mining, and analysis. MATLAB's Neural Network Toolbox was straightforward to use, and was highly flexible to meet our varying needs and shifting requirements. The following discussion pertains only to results obtained with MATLAB.

A MODIS data set consisting of 25,713 samples was assembled, in which the ratio of fires to nonfires was approximately 1:1. A variation of the cross-validation technique was employed for training and testing. The total collection of available fire hotspot pixel patterns was divided into 4 quarters, each being representative of the entire data set. One-half of the total number of patterns constituted the neural network training set; one-quarter were relegated to a validation set; and one-quarter were assigned to a test set – thereby resulting in 3 disjoint data sets. Batch training using the "Gradient Descent with Momentum" algorithm was selected from a suite of the available MATLAB routines. To prevent overfitting, early stopping was employed – during training, the mean squared error on the validation set was monitored – when it began to rise, training was automatically halted. Testing then continued on data (the test set) that had not been seen at all by the neural network during the training and validation phases.

Neural network classification results were initially formulated as error matrices from which a statistical analysis was derived. Since a simple 2-class system was involved (fires and non-fires), empirical error matrix data consisted of: true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). Four measures of classification accuracy in terms of these parameters are shown below for the MODIS sensor:

Overall Accuracy	(TP+TN)/(TP+TN+FP+FN)	= 92.36 %
Producer's Accuracy (fire)	TP/(TP+FN)	= 89.91 %
Producer's Accuracy (nonfire)	TN/(FP+TN)	= 94.72 %
User's Accuracy (fire)	TP/(TP+FP)	= 94.25 %
User's Acuracy (nonfire)	TN/(TN+FN)	= 90.70 %

Producer's Accuracy measures the accuracy with which the network labels a known (HMS-identified) fire as a fire (Class 1), and labels a known (HMS-identified) nonfire as a nonfire (Class 0). User's Accuracy measures the accuracy with which a user can confidently assume that a labeled fire (Class 1) is a real (HMS-identified) fire, and assume that a labeled nonfire (Class 0) is a real (HMS-identified) nonfire. Overall Accuracy measures the percentage of correct fire/nonfire classifications produced by the trained neural network model.

Generally, a high degree of classification accuracy was achieved for the MODIS and AVHRR sensors, while classification of GOES image data performed relatively poorly. This was attributed to the accuracy of the science instruments themselves as well as the refinement in fire detection algorithms which followed the earlier GOES methods.
The original intent of the project was to generate a single neural network model that could: (a) process sensor data from all three instruments (MODIS, AVHRR, and GOES); (b) perform fire classification at least as well as the automated algorithms and NOAA's human fire analysts currently achieve; and (c) be incorporated into NOAA's operational Hazard Mapping System – to reduce the amount of manual intervention needed to generate a global fire product. However, our research has shown that there was insufficient (often non-existent) temporal and spatial overlap between the three sensors to process imaging data with a single network. Even excepting this problem, the extreme size of the network, exacerbated by 7x7 pixel arrays to characterize fire patterns, would have made training difficult or impossible for our host platform. Our work showed that dividing processing between 3 independent networks was the practical solution and that GOES data should probably not be processed at all by the neural network because of the low classification accuracy. Some improvement in classification accuracy is believed likely by incorporating in the training process additional generalization techniques such as Modified Performance Function and Bayesian regularization. Perhaps then, with further research efforts, the neural designs could be incorporated into an operational system and relieve the amount of manual intervention in NOAA's fire detection procedures.

References

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