Technical Disclosure Commons

Defensive Publications Series

February 2020

Machine-Learning Based Smoke Detection

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MACHINE-LEARNING BASED SMOKE DETECTION

BACKGROUND

Conventional smoke detectors use a threshold to determine when an amount of measured smoke is sufficient to trigger an alarm or warning being output. Some situations may result in “nuisance” alarms being output in which the threshold is exceeded, but no emergency is present. This problem may be exacerbated by new regulations that require a smoke alarm to sound based on the rate of change of measured smoke. For instance, cooking may generate sufficient smoke to result in an alarm being output by a smoke alarm even though no emergency is present.

DESCRIPTION

A machine learning based arrangement can be used to more accurately detect whether a smoke alarm should be sounded based on a determined rate of change in the measured amount of smoke. During a fire for which a smoke alarm should be sounded (a “true alarm situation”), measured smoke may initially increase at an exponential rate. For a nuisance condition during which a smoke alarm should not be sounded (a “false alarm situation”), smoke may tend to not increase at an exponential rate. Once a relatively high amount of smoke is present, the increase in smoke may be approximately linear for both true and false alarm situations. Therefore, the initial exponential increase can be used to differentiate true and false alarm situations.

In order to perform such differentiation, a machine-learning algorithm may be evaluated, such as Equation 1, that learns the linear classifier coefficients that represent the features of a true alarm situation. The machine-learning algorithm may be pre-trained before being installed on various smoke detectors. Therefore, the algorithm may be pre-trained before manufacture of the smoke alarms. Alternatively, the pre-trained model may be loaded onto smoke detectors already present in the field, such as via network connections of the smoke detectors.

In Equation 1, *v* represents the buffered optically-measured smoke signal (indicative of the amount of smoke present in the environment) and *T* represents the score threshold that can be used for decision making as to whether a true alarm or warning condition is present. In other embodiments, the smoke signal may be obtained from a source other than an optical sensor.

$$s^T v > T \qquad \textbf{Eq. 1}$$

In order to determine whether a true alarm condition is present, multiple values of *v* may be analyzed that were gathered over time. Coefficients s^T represent the weighting applied to the values of *v*. Therefore, $s^T v$ can represents a dot product that is obtained by multiplying each weighting vector by the corresponding time-based smoke measurement. The value of T may be set after the values of the coefficients s^T are determined and can be used as a threshold to determine if a true alarm or warning condition is present.

Based on the assumption that exponential trends can appear locally linear, the classifier coefficient can be parametrized to reduce overfitting and the computational complexity of the machine learning process as defined in Equation 2. That is, rather than attempting to identify a large number of coefficients, the calculation of s^T can be simplified into two linear slopes, thereby only requiring two values, a_1 and a_2, to be calculated.

$$s_i = a_1 * if(i < 0) + a_2 * if(i \geq 0) \qquad \textbf{Eq. 2}$$

A machine learning process may be performed in order to minimize $a_1$and a_2. Equation 3 may be used to solve the least-squares optimization problem:

$$minimize(a_1, a_2) \sum_i ||s(a_1, a_2) - v_i||_2^2 \qquad \textbf{Eq. 3}$$

In Equation 3, v_i indicates the i*th* sample data vector. This regression problem can be solved using a two dimensional grid search, such as represented in FIG. 1. The optimal learned linear coefficient model of Equation 3 can penalize matching filtering scores on consistent linear ramps for both positive and negative datasets, but boosts the score during the initial exponentially trending period. Since the initial exponentially trending period is only present during true alarm situations, the score is increased for true alarm situations but not false alarm situations. In FIG. 1, the values of a_1 and a_2 (not illustrated) corresponding to the lowest error value (1, in the illustrated grid), can be used as a linear substitution for the values of s^T. FIG. 2 represents an example of learned coefficients for N=13.

This arrangement can result in strong score separation between true alarm situations and false alarm situations. Once the two values of s^T have been set, a value of T can be set that differentiates true alarm conditions from false alarm conditions. By setting *T* to around 5 in one example, tested true alarm conditions can be distinguished from false alarm conditions. While various ways of determining T are possible, one possible way of finding T is taking an average of the value of the two closest in magnitude true and false alarm conditions. This average can yield a value of *T* that is between the two closest true and false alarm conditions.

Once trained, the pre-trained model can be implemented on a smoke alarm or combination smoke alarm and carbon monoxide alarm to distinguish between true and false alarm situations based on the rate of change of the measured amount of smoke. For false alarm situations, an announcement may be made, such as using synthesized speech, that indicates that no alarm is being sounded even though smoke is present because a false alarm situation has been detected. For a true alarm situation, a warning may first be output, such as an indication that smoke levels are rising, followed by a loud alarm. Alternatively, a loud alarm may be sounded immediately without an initial warning for a true alarm situation.

In some situations, the smoke alarm may be network-enabled and may communicate with a remote server. The remote server may provide services, such as updates to the pre-trained machine learning model to allow the smoke alarm to more accurately differentiate between true and false alarm situations.

The smoke alarm may include one or more processors capable of executing the pre-trained learning model. One or more smoke sensors may be incorporated as part of the smoke alarm. Such smoke sensors may be ionizing smoke sensors or optical smoke sensors.

ABSTRACT

A machine learning based arrangement can be used to more accurately detect whether a smoke alarm should be sounded based on a determined rate of change in the measured amount of smoke. The machine learning model may be pre-trained based on training data then executed by a smoke detector to accurately distinguish between likely emergencies and nuisance conditions.

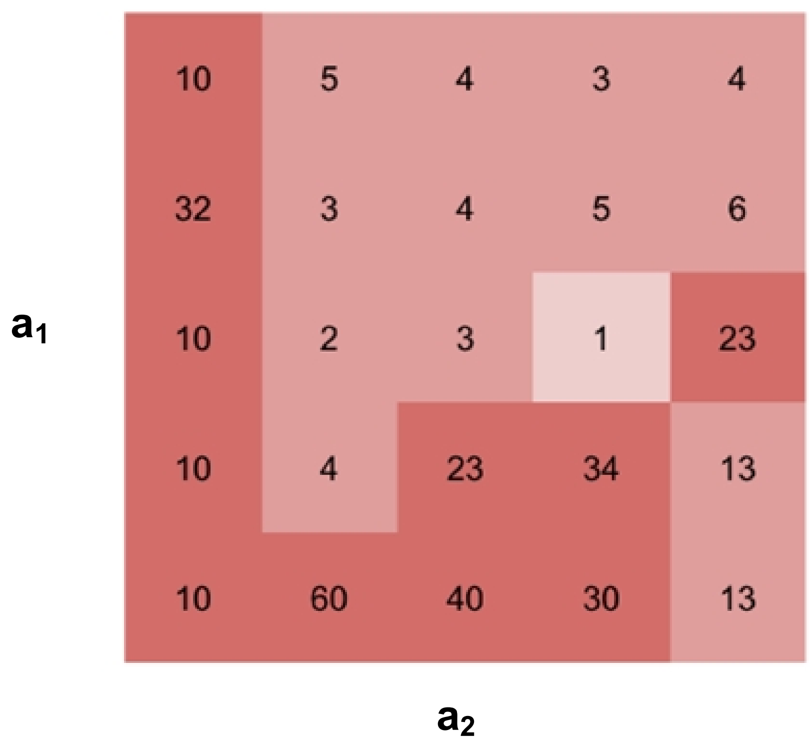
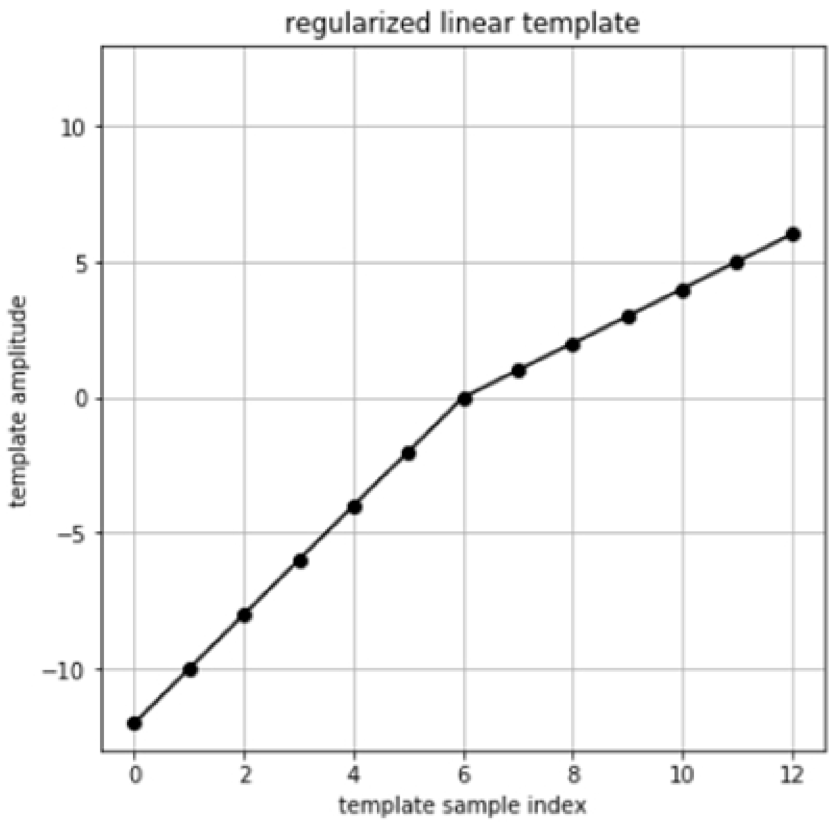


FIG. 1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template amplitude
template sample index
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5
0
−5
−10
0
2
4
6
8
10
12

FIG. 2

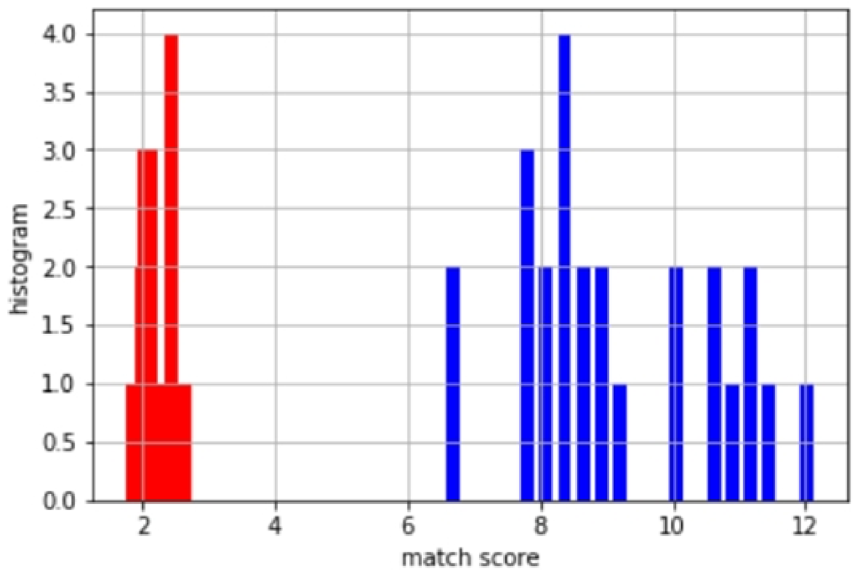

FIG. 3