Study The Fire Detection Method Using Support Vector Machine

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Abstract

Fire detectors are designed to detect fires at an early stage and to reduce of false alarms. Unfortunately, it's not always possible to completely prevent false alarms.

In this study, we examined the possibility of improving detection-performance and reducing false alarms by combining Artificial Intelligence (AI) technologies.

We created a fire judgement method using a Support Vector Machine as an AI model. It discriminates between fire and non-fire factors; it was confirmed that it was effective for early detection of fire and the reduction of false alarms.

Keywords: Fire detection, Multi-sensor, False alarm, Machine learning, Artificial Intelligence (AI), Support Vector Machine

Introduction

A general-purpose fire detector has a simple process for judging fire occurrence when a sensor output value, smoke density or temperature, exceeds a predetermined threshold value. A smoke detector detects smoke particles generated from a fire by using an optical method. Unfortunately, it also detects other particles such as steam or spray, which can cause the problem of false alarms.

Artificial Intelligence (AI) has allowed to automatically find rules and judgment criteria from vast amounts of data and automatically enhance the judgment and prediction capabilities equivalent to human ones.

We examined the possibility of improving detection-performance and reducing false alarms by combining an AI technology.

Method

SVM processing conditions

Fig. 1 shows an outline of the processing for a fire detection method using an AI model. In this study, we used Support Vector Machine (SVM: one of the methods of machine learning) [1] as an AI model.

SVM is a pattern recognition model and forms a discriminant model (boundary surface) of each class so that the distance to each point of the learning data is maximized. Unknown data is used as an input to the discriminant model, and classification is performed according to the value with the largest distance from the boundary surface. The discriminant model of SVM is expressed by a linear expression in which input elements are multiplied by weighting factors and added for each class. The processing part of SVM in this study used the open source library of machine learning (scikit-learn) [2].

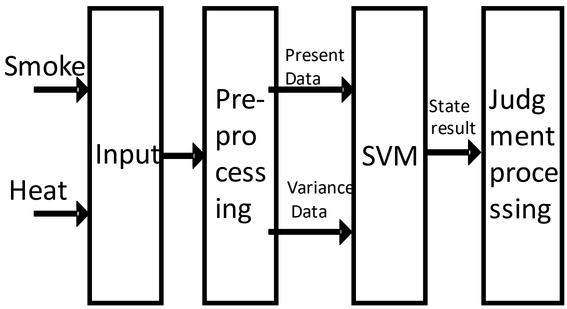


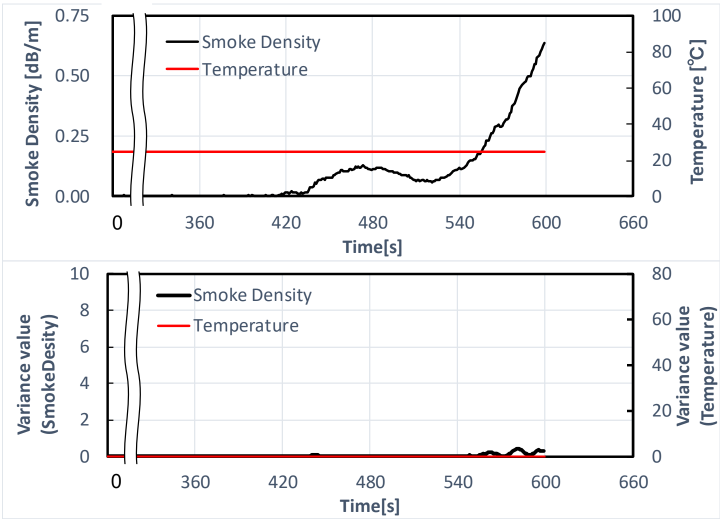
Fig. 1. Outline of the processing using SVM.

Input elements to SVM

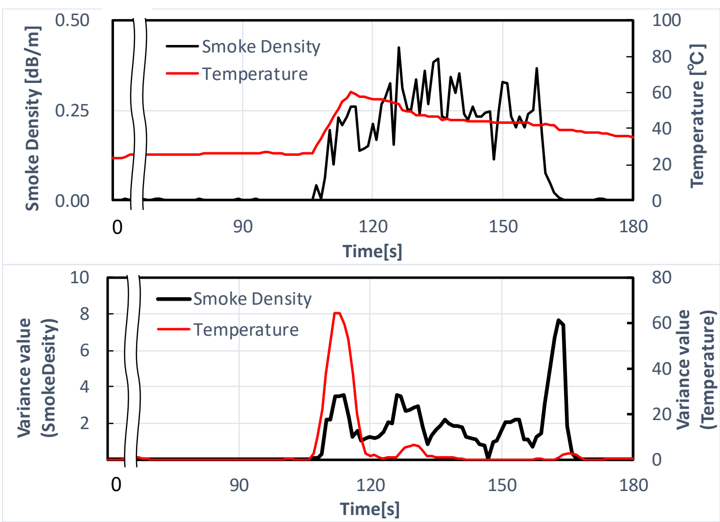
Smoke density and temperature values are inputs to the SVM. Smoke density and temperature values were obtained with a fire detector (Hochiki, Multi Sensor Detector (Heat & Smoke), ACC). As supervised signals for the SVM, we determined “Normal state”, "Fire State", and “Non-fire State”. The SVM learned smoke density and temperature values obtained from the fire tests [3] and non-fire factor reproduction experiments. For the SVM learning, a total of 57 cases (42 cases: Fire Test, 15 cases: non-fire test) of experimental data were used. Conditions for judging a fire were built based on the SVM discrimination result.

In order to consider input elements to the SVM, fire tests and non-fire factor reproduction experiments (steam, shower, cooking, tobacco, and hair spray injection) were conducted. Fire test data was captured were acquired at a horizontal distance of 3 m from the fire source within the test room (10 m x 6 m x 4 m) according to ISO standard [3]. Non-fire factor reproduction experiments were reproduced in an environment simulating a typical living room.

As a characteristic the smoke density of the detector output in non-fire factors temporarily rose sharply or large fluctuations were observed. On the other hand, the smoke density of the detector output tended to increase gradually during the fire tests. We focused on the trend of these characteristics. In order to input these characteristics into SVM, we examined the past values, differential values, integral values, and variance values. In this study, we used the variance value that gave the most accurate SVM learning results.



(a) Fire test (TF2 : wood smoldering)



(b) Non-fire test (steam from the bathroom)

Fig. 2. Smoke density and temperature values, and variance values.

Fig. 2 shows smoke density value and variance value of over a pre-determined time period. In case of fire test(a), the smoke density value gradually rose, and the variance value shows a small value (less than 1). In the case of non-fire test (b), the fluctuation of the smoke density value is large, and the variance value (maximum 7) is higher than fire test, and the change tended to be large. In this study, smoke density and temperature values and the variance values of three different time widths were used as input to SVM.

Fire judgment processing

In the fire judgment of a fire detector, the smoke density value is corrected, and the accumulation time (time until fire judgment) is changed based on the SVM discrimination result (Table 1). If SVM determined that there is "Fire State", the smoke density value is corrected to a higher value so a fire judgement can easily be made. If it is discriminated that “Non-fire State”, smoke density value is corrected to a lower value, and the accumulation time is longer, therefore it is difficult to judge this as the fire. If the corrected smoke density value exceeds the threshold value and the accumulation time has elapsed, it is judged as a fire.

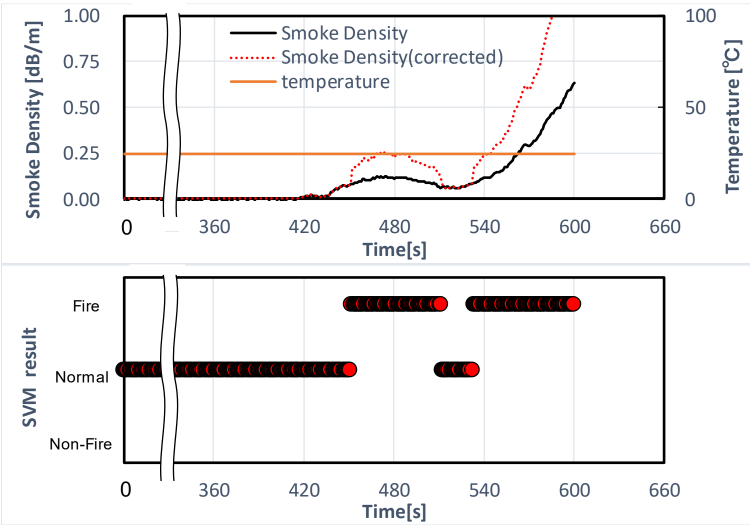
Table1. Condition for smoke density value correction, and the accumulation time for SVM discrimination result.

Discrimination result	Correction factor	Accumulation time
Normal State	1.0	3 sec
Fire State	2.0	3 sec
Non-fire State	0.6	15 sec

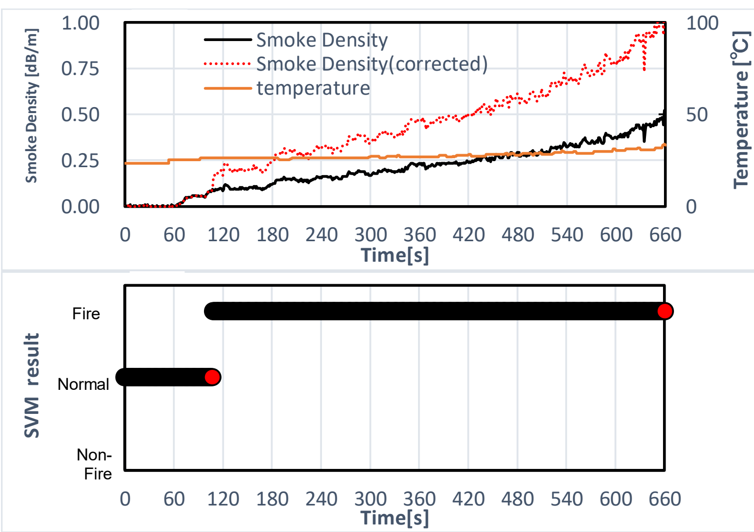
Result and Discussion

SVM judgment result

The verification was performed using the data excluded for SVM learning. When the smoke density of the detector starts to increase gradually in Fig. 3 shown as fire test, the smoke density of the detector is corrected to higher value as a "Fire State" by SVM. Therefore, the detector generated an alarm earlier than the existing fire detector.



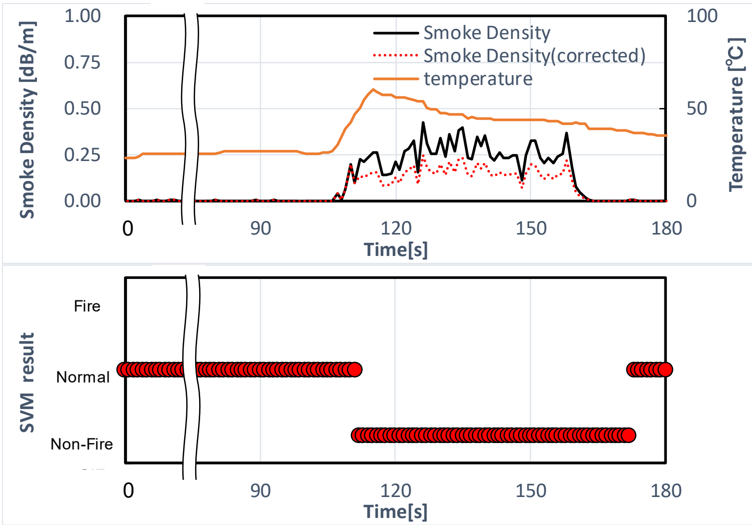
(a) TF2 : Wood smoldering



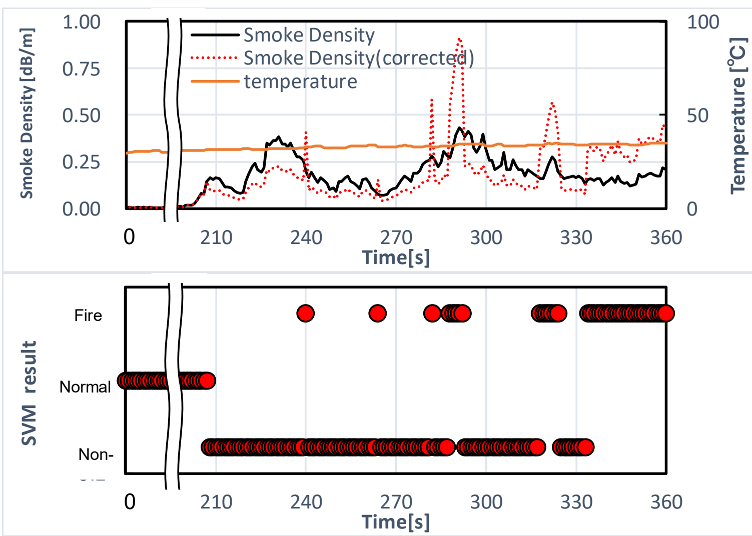
(b) TF8 : Decalin flaming

Fig. 3. SVM discrimination result and smoke density (fire test).

The section where the smoke density of the detector has large fluctuations in Fig. 4 shown as non-fire test, the smoke density of the detector is corrected to lower value as a “Non-fire State” by SVM. Therefore, it prohibits false alarm due to those factors.



(a) Steam from the bathroom



(b) Cooking grilled meat

Fig. 4. SVM discrimination result and smoke density (non-fire test).

Comparison of Detection time

Fig. 5 shows the response time of the existing detectors (Smoke, Smoke･Heat multi, Smoke･Heat･CO multi), and the fire judgment processing of this study was applied. As a result of the verification, response time of the fire test by this study tended to be shorter than those of the existing detectors. In case of non-fire test, the detector with SVM did not generate any an alarm even if the existing detector generated alarm under same conditions. In this study, we obtained a positive result that the detector shows an improvement against false alarms.

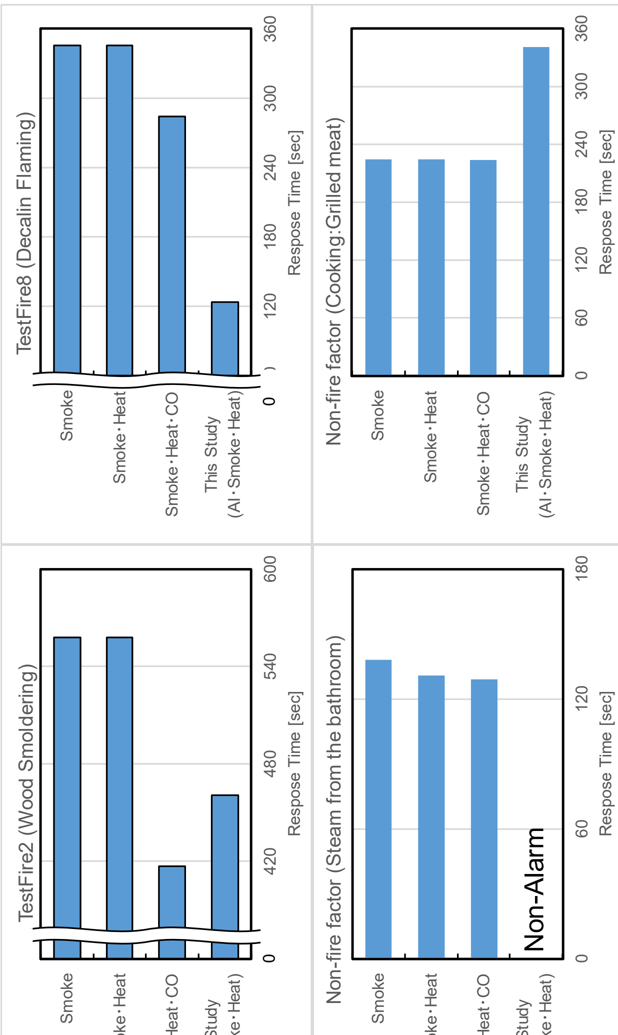


Fig. 5. Response time of fire detectors.

It was confirmed that this method is effective in reducing false alarm in situations where the smoke density of the detector fluctuates for instance, steam from a shower. However, even if the SVM discriminates that it is a false alarm, and the corrected smoke density is of a low value, it continues to operate by continuing fire determination threshold for accumulation time or longer. Therefore, it is not possible to completely eliminate false alarms due to every factor. In this verification, it was confirmed that time until activation could be delayed when compared with the existing detector, and the reduction of false alarm was improved.

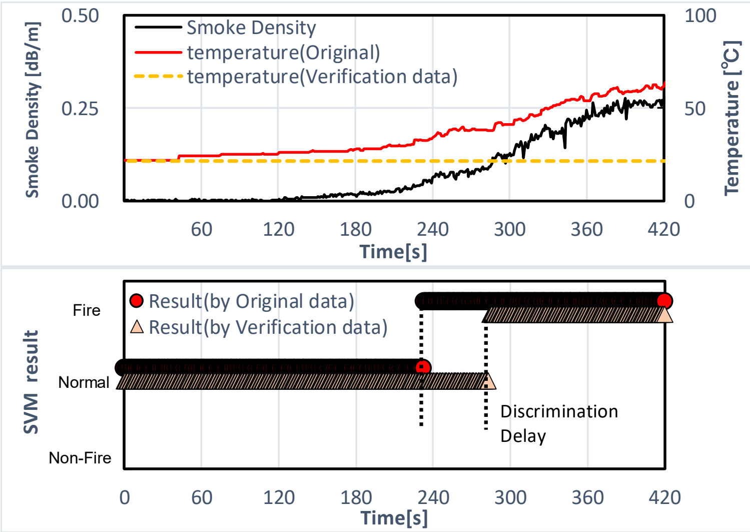
Consideration of SVM input elements and discrimination results

The SVM discriminates the class as the most value in the primary equation multiplied by a weighting factor to each input element for each class. Weighting factor for each input element is larger in the positive affects the SVM discrimination result of each class.

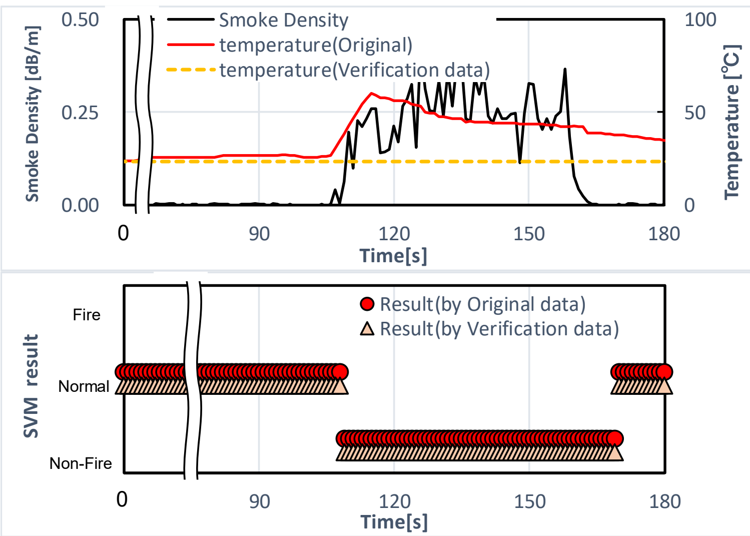
In the SVM learning result in this study, the weight coefficient of the class "Fire State" is larger in the order of smoke density and temperature. The higher the smoke density or temperature, the more it is judged as a class "Fire State". Further, the weighting factor of variance value is negative value, and the higher the variance value, the more difficult it is judged as a class "Fire State". On the other hand, the weight coefficient of the class “Non-fire State”, variance value of smoke density is high weight coefficient, the weight coefficient of temperature is almost zero. Therefore, the impact on the “Non-fire State” discrimination high influence of the variance value of smoke density, influence of temperature is small.

We verified the effect of temperature input on discrimination. In the verification, the difference in the discrimination result was confirmed by inputting to the SVM what was obtained by virtually eliminating temperature value change of the verification data (as a condition that there was no temperature change from the initial temperature).

Fig. 6 shows an example of the verification results for fire test and non-fire test. In the data of fire test (a), the result of the SVM discrimination was delayed in fire test (Ex. TF1, TF5, TF6) in which the temperature change occurred when temperature change was eliminated. Especially for fire sources with low smoke density and high temperature, it is considered that smoke density and temperature value are effective for early detection of fire by using SVM as input elements. Regarding the non-fire factor (b), even if the temperature change is eliminated, there is no difference in the determination result, and the influence of temperature value tends to be small in the discrimination of “Non-fire State”.



(a) Fire Test (TF1 : Wood flaming)



(b) Non-fire test (Steam from the bathroom)

Fig. 6. Effect of input element (temperature) on discrimination.

Conclusion

We created a fire judgement method using SVM as an AI model. It discriminates between fire and non-fire factors such as steam and tobacco, it was confirmed that it was effective for early detection of fire and the reduction of false alarms.

In the future, to improve discrimination performance of SVM, and respond to not only the test fire but also an actual fire, and to improve the reduction of false alarms, it is necessary to collect data of the detector output and learn and verify the SVM. Also, we will also give further consideration for the early detection of fire and the reduction of false alarm by optimizing the fire judgment processing according to the SVM judgment result.

Reference

[1] C. Cortes and V. Vapnik, *Support-Vector Networks*, Machine Learning, 20(3):273-297, September 1995.

[2] scikit-learn developers, sklearn.svm.SVC, [https://scikitlearn.org/stable/modules/generated/sklearn.svm.SVC.html],(16/4/2020).

[3] ISO/TS 7240-9:2012 Fire detection and alarm systems -Part9:Test fires for fire detectors.