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Influence of Feature Extraction Duration and Step Size on ANN based Multisensor Fire Detection Performance

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Abstract

ANN has displayed great advantage in multisensor based fire detection. One of the major application steps in application of ANN in multisensor fire detection is feature extraction of time series. The objective of this research is to investigate feature extraction window duration and step size on fire detection performance. Some experimental results are adopted as benchmark tests, and detected fire time and failed alarm rate are the important indicators of performances. Three ANN types, namely BP, RBF and PNN are analyzed. Results indicate that both observation window duration and step size can determine ANN fire detection performance to a large extent, and a duration period of 90s with time step varies from 25s to 200s is recommended. Meanwhile, PNN might be the favorable ANN types related to the two performance parameters.

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Keywords: multisensor fire detection; artificial neuron network; dynamic observation window; step size

1. Introduction

Fire detection system is required in many types of buildings. Purpose of fire detection system is to launch efficient alarm for evacuation before a building develop to a threaten situation for people[1], because evacuation is a measure that can reduce disaster losses in many aspects[2, 3]. Early fire detection can provide relatively long available egress time for residents, and can assist efficient fire control. Performance of early fire detection is thus one of the major concerns of a fire detection system. However, nuisance false is another serious problem related to fire detection[4]. Frequent false alarms can result in switching off of fire detection system. The relevant building is thus exposed to a situation of no fire protection system.

Therefore, there is always a tradeoff between false alarm rate and failed alarm rate. Principle of development of new fire detection technology is to investigate possible measures to reduce false rate and failed alarm rate and to increase fire detection sensitivity as well [1, 5].

Performance of multisensor technology is widely reported to have superior performances compared to those of single sensors [6-9], and even is deemed to be the next generation of fire detection technology[10]. One major issue in multisensor fire detection technology is information fusion algorithm to combine time-dependant information from various sensor sources. Artificial Neural Network (ANN) is a prevent algorithm among all fire detection information fusion measures, due to its outstanding capacity in pattern recognition, classification and curve fitting, which is widely reported in many fields.

Multisensor information fusion related to various sensor sources is essentially a time sequence. Simply input all data sampled simultaneously at an instance into ANN may generate high false alarm rate and failed alarm rate. A preferable method is to extract a fixed time sequence of the entire sensor information as ANN inputs. Though repeated efforts are

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devoted to application of ANN in multisensor based fire detection technology, rare information is available about influence of feature extraction duration and moving observation time step on multisensor fire detection performances.

The objective of this research is to investigate performances of multisensor fire detection technology related to various feature extraction duration and moving time steps of observation windows. Performances of fire detection technology include failed alarm rate and false alarm rate, summery of both will be referred to as wrong alarm rate, and detected fire time.

2. Methodology

2.1. Benchmark Experimental Results

National Institute of Standards and Technology (NIST) conducted a series of tests to examine performances of different fire alarm types to residential fire settings[11]. All tests were performed in two scenarios: one is in a manufactured room and the other is in a two story house. In this research, we adopted some test results from the experiment numbered SDC01 in the report in the manufactured room as benchmark experiments.

Schematic arrangements of the manufactured room are illustrated in Fig. 1. Dimension of the home is 84.7 m2, and it is consisted of three bedrooms, one full bathroom, one kitchen/dining area, one living room, and two hallways. Detailed arrangements and descriptions of the experiment can be referred to the report. In our current research, recorded fire parameters from spot A are analyzed.

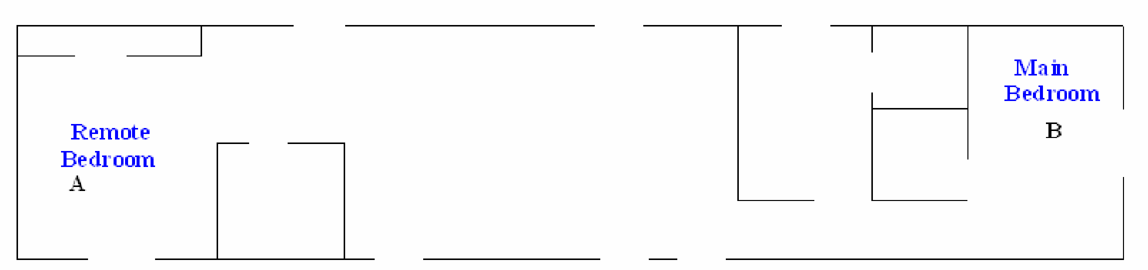

Fig 1. Instrumentation Installation Positions (modified from [11])

The sensors include a thermocouple 900mm below ceiling, a smoke obscuration sensor, one sensor of CO and CO2. Thermocouple was bare-bead K type specifically which were constructed from 0.25 mm diameter wires. Smoke obscuration sensor was laser based light extinction measurement devices. CO and CO2 measurements were conducted using nondispersive infrared (NDIR) analysis. All devices were calibrated rigidly before each test. Recorded data of all sensors during experiment process is shown in Fig. 2.

2.2. Structure of ANN based Fire Detection Technology

Application of ANN in multisensor fire detection technology typically is consisted of four parts: Data Acquisition, Signal Preprocessing, Feature Extraction and Classification. The structure can be depicted in Fig 3.

Data Acquisition is to record analog or digital signals of various sensors. For analog signal, some transformation is needed sometimes to convert current or voltage signal into values of physical variables. The second part is preprocessing of the recorded signals. Zero-drift is usually unavoidable, and some random fluctuations (noise) may be incorporated into the signal due to dynamic measuring environments. Wavelet fit is adopted to filter out noise signals. Normalization is performed to avoid signals be overwhelmed by noises related to maximum and minimum measured results. Then a characteristic part of the signals was extracted from beginning of the recorded parameters to a point when all four variables' values reach the maximum. Treated results are shown in Fig 4.

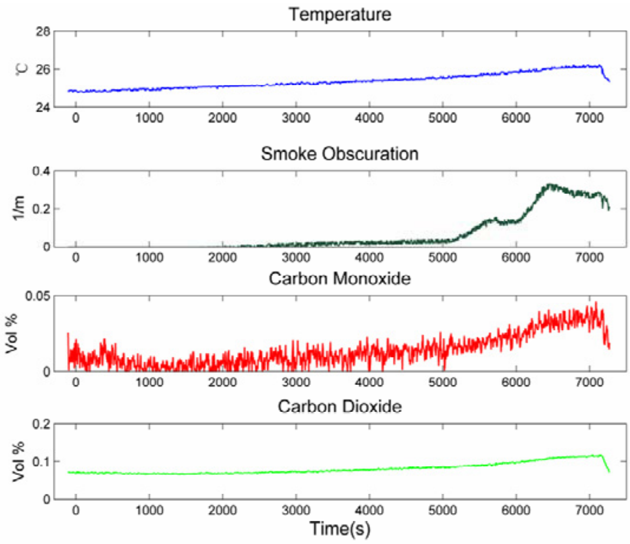

Fig 2. Recorded data of all sensors during experimental process

Fig 3. ANN based multisensor fire detection process

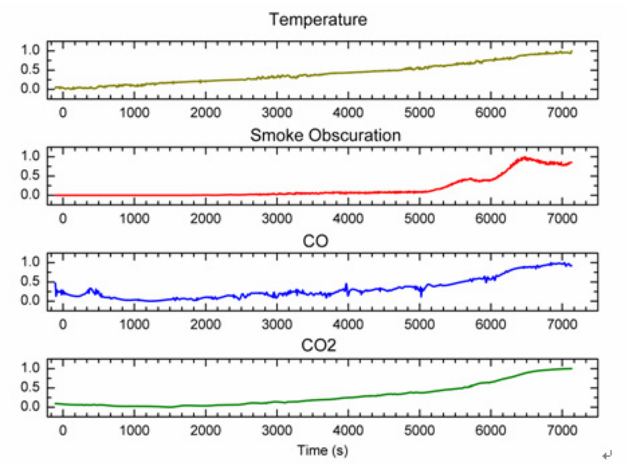

Fig 4. Normalized Signals of Extracted Characteristic Parts

2.3. Feature Extraction with Moving Observe Windows

Fire detection using ANN is a dynamic process, in which the limited information in time sequences should be taken into consideration. Feature extraction is important for detection accuracy. As is shown in Fig 5, fluctuations in localized area may be too dramatic to overwhelm the trend, and inputting the instant sensor variables into ANN is prone to generate a high wrong alarm rate. The most popular method in ANN fire detection is to differentiate fire patterns with a moving observation window as is depicted in Fig 5.

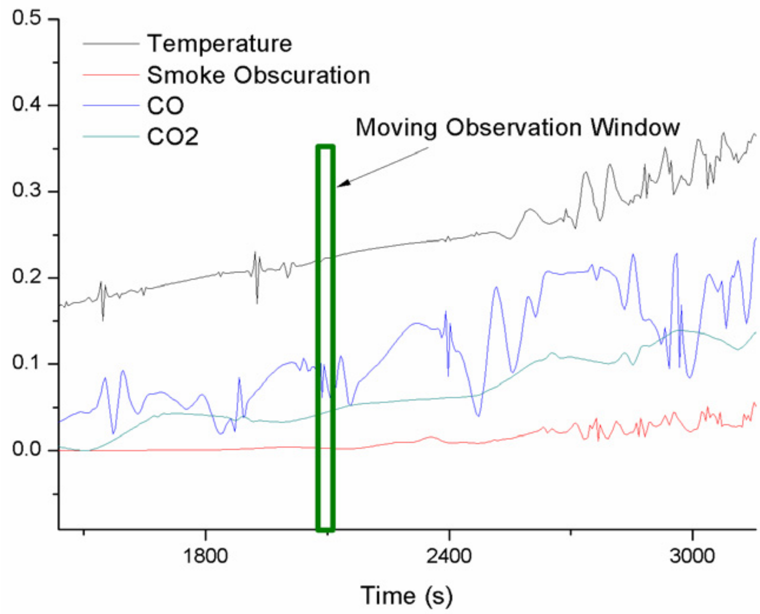

Fig 5. Application of Observation Window in Feature Extraction

However, duration of the moving observation windows can thus affect detection results dramatically. In this research, durations of 30s, 60s, 90s and 120s were adopted to analysis observation windows' influence. For consistence of application of ANN, both training process and testing process of ANN used the same observation window duration.

Another parameter is moving step size of the observation window. For training process, this will determine ANN calculation efficiency. A short step size I deemed to result in precise detection result but long training period and testing period. Another problem is that too much training data may induce overtraining problem and reduce detection accuracy. A long step size may not generate enough fire patterns for ANN to recognize similar fire situations, though calculation efficiency can be improved. In this investigation, step size with a large range from 10s to even 2000s was studied to illustrate influence of step size in fire detection accuracy. The shortest 10s is essentially the same as testing step size.

Two parameters are the major concerns in fire detection results in this research. One is wrong alarm rate, which is the summery of false alarm rate and failed alarm rate during the entire calculation process. The other is detected fire point, and this is to illustrate the point when fire is detected by ANN. Wrong alarm rate is used to indicate fire detection performance of reliability, while detected fire point is adopted to test fire detection performance of sensitivity.

For convenience, detected fire point is used instead of detected fire time. Sample rate in the experiment is 1 Sample/5s. From Fig. 4 it is found that apparent fire signature appears around 1500s, then with a training step size of 10s, the expected accurate detected fire point is around 150, but may vary a bit due to various durations of observation window. It should be noted that the lowest value of detected fire point is 127, if the result is 127, it does not mean that high sensitivity is obtained, but high wrong detection rate appears, which mistaking non-fire situation for fire.

3. Results and Discussions

3.1. Calculation Results of an Individual Case

Fig 6 depicts an ANN fire detection results under a parameter condition with observing window duration of 60s and step size of 100s. It can be seen that PNN has precise fire detection result, no false alarm and failed alarm is found, and the according wrong alarm rate is 0. Detected fire point is 140, which is earlier than expected 156. This is mainly because PNN has the capacity to identify similar untrained pattern with known knowledge, and the period from point 140 to 156 is similar to fire situations of periods after point 156. The expected point 156 is mostly subjective with our own observation, and from PNN results it is deemed that the critical point may be better with an earlier point.

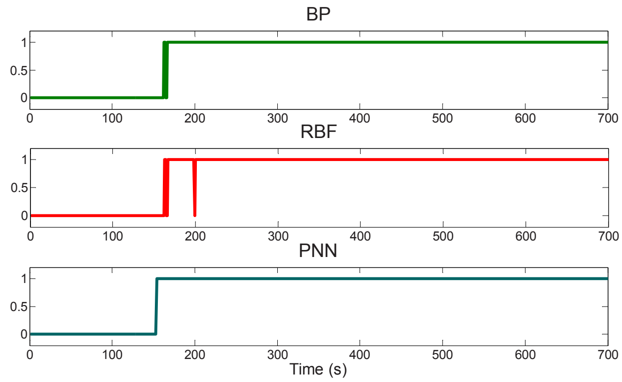

Fig 6 ANN Fire Detection Results with Duration of 60s and Step Size of 100s

The detected fire point for BP and RBF is 165 and 163 respectively, and the according wrong alarm rate is 0.0029 and 0.0043. Algorithms for calculation of detected fire point is to search from point 127 to find the earliest critical point when continuous ten points are detected to be fire. Wrong alarm rate is to calculate detected fire point between the critical point and detected non-fire point after the critical point related to the entire point sequence. If the detected fire point is earlier than point 127, then it is deemed to be 127 and those earlier states will be calculated as wrong alarm. The algorithm is selected from many various algorithms, and has the advantage to discriminate detected fire point from wrong alarm rate calculation. Calculation process is similar in the following individual cases.

3.2. Influence of Window Duration and Step Size on Fire Detection Results

(1) Influence of Step Size

Observation window duration of 60s is specified to investigate effects of feature extraction step size on fire detection results. Fig 7 and Fig 8 maps results of wrong alarm rate and detected fire points of the selected three ANN models under various time steps respectively. It can be found that false alarm rate increases with increase of step size, especially when step size is over a critical point. For PNN, the critical point is around 100s, while for the other two around 300s. However, for the step size below 100s, PNN displays a lower wrong alarm rate than the other two. For simplicity, step size is not preferable for the three ANN models related to wrong alarm rate with duration of 60s.

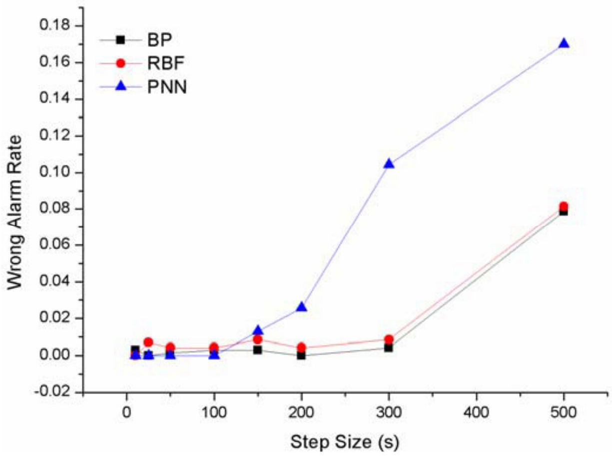

Fig 7 Wrong Alarm Rate of ANN Models of Various Step Sizes with Duration of 60s

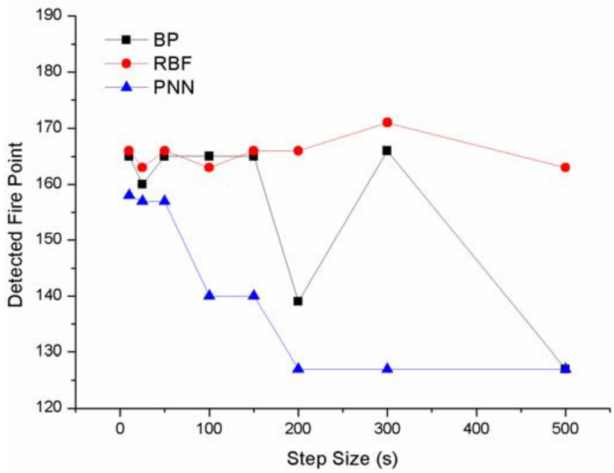

Fig 8 Detected Fire Point of ANN Models of Various Step Sizes with Duration of 60s

Detected fire point of PNN decreases dramatically with increasing of step size. When the step size increasing over 200s, detected fire point of PNN is point 127, which implies that PNN will not be able to differentiate fire from non-fire. Step sizes below 150s are favorable for PNN. RBF displays a steady trend in detected fire point with increasing step sizes. Performance of BP fluctuates a lot when step size is over 150s. Step size below 150s may be favorable related to detected fire point of all the three ANN models with observation duration of 60s.

(2)Influence of Observation Window Duration

A specific step size of 50s is selected to further investigate influence of observation duration on fire detection results. Four different duration fire detections, namely 30s, 60s, 90s and 120s, using various ANN models were conducted. Results of wrong alarm rate and detected fire point are shown in Fig 9 and Fig 10 separately. No apparent variation of wrong alarm rate of BP and RBF can be found of the four durations, and both maintain a low wrong alarm rate level. Wrong alarm rate of PNN changes dramatically. There is essentially no wrong alarm with duration of 60s and 90s for PNN, which is superior to both RB and RBF. However, PNN fails to distinguish fire from non-fire when duration changes to 30s and 120s. This implies that PNN is sensitive to observation window duration, and too long or too short duration may results in high wrong alarm rate, while BP and RBF may be not too sensitive to duration with a precondition of the specific step size.

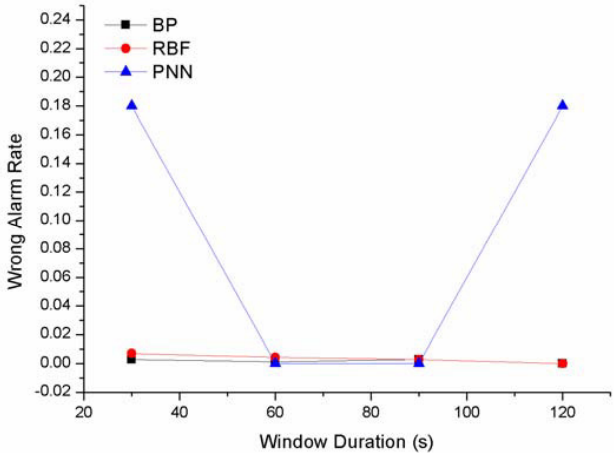

Fig 9 Wrong Alarm Rate of ANN Models of Various Durations with a Step Size of 50s

As is depicted in Fig 10, detected fire points for BP and RBF varies a little, all are around the expected point though there may be some slight fluctuations. However, for PNN, the detected fire point is earlier than both BP and RBF with duration of 60s and 90s, which implies that PNN has better fire detection sensitivity than the other two in this specific condition. But when duration changes to 30s and 120s, PNN fails to distinguish fire and non-fire. This illustrates that fire detection sensitivity of PNN depends on duration to a large extent.

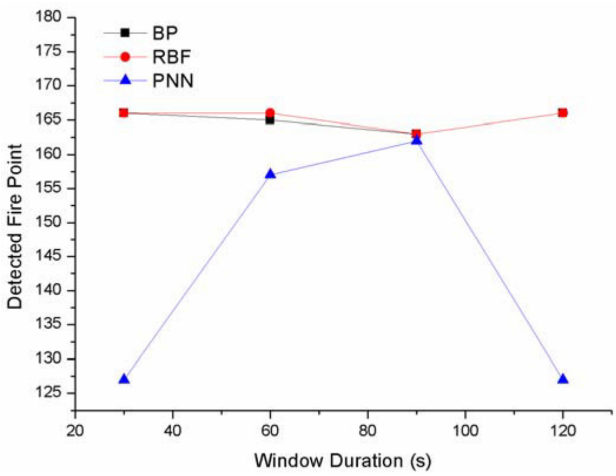

Fig 10 Detected Fire Point of ANN Models of Various Durations with a Step Size of 50s

3.3. Effect of Various Step Size and Duration on Different ANN Models' Performance

It is found from the above analysis that performance of various ANN models may vary dramatically with the same observation window duration and step size. Then performance of different ANN models with different durations and a relatively long range of step size are investigated in this part.

Fire detection results of BP are shown in Fig 11. Fig 11(a) maps the wrong alarm rate results while Fig 11(b) depicts the detected fire point results. It can be seen that wrong alarm rate varies to a small range when the step size is less than 250s for all four durations. However, when step size increases, some high wrong alarm rate is found for duration of 60s. Performances of duration of 90s need to be addressed; from 250s to 2000s, relatively nearly no wrong alarm rate is found. Satisfied detected fire point results are found for all durations in nearly all investigated step sizes, except that for duration 60s with the step size near 500s; the ANN model fails to differentiate fire from non-fire.

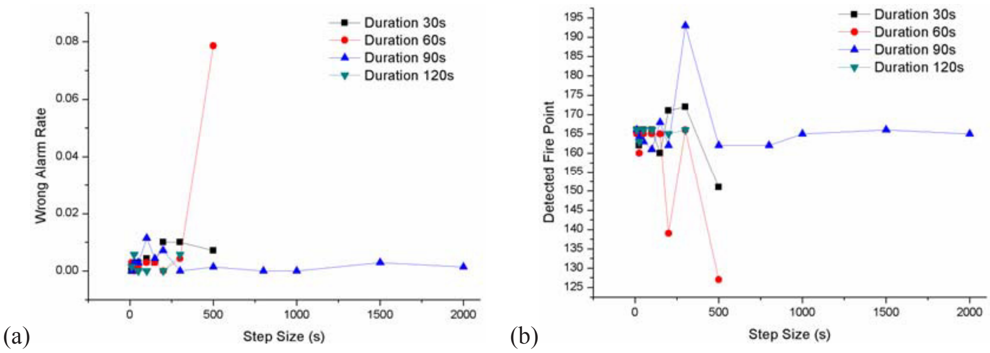

Fig 11 BP Fire Detection Performance under Various Durations and Step Sizes for (a) Wrong Alarm Rate (b) Detected Fire Point

Performance of RBF with various observation window duration and step size is shown in Fig 12. The overall trends of both wrong alarm rate and detected fire point are similar to those of BP. Performance of duration 90s in wrong alarm rate is outstanding. Nearly all durations with investigated step sizes obtain satisfied fire detection sensitivity results.

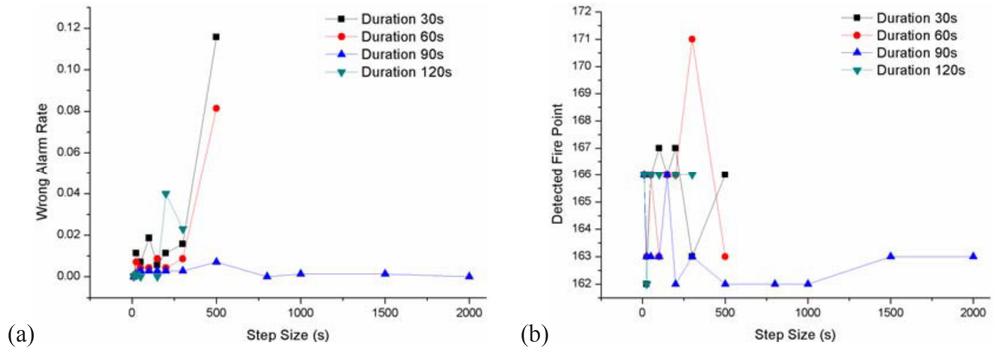

Fig 12 RBF Fire Detection Performance under Various Durations and Step Sizes for (a) Wrong Alarm Rate (b) Detected Fire Point

Relevant fire detection results of PNN are shown in Fig 13. PNN is more sensitive to changes of step size than BP and RBF for duration 30s and 120s. For duration 60s, when step size is less than 100s, no wrong fire alarm is found. But when step size increases further, wrong fire alarm rises quickly. PNN model with duration 120s might be the best candidates of all investigated combinations. Astonishing no wrong alarm rate is found with a step size from 10s to 1500s, and the detected fire point is also satisfied. This PNN is more sensitive to duration selection, and a narrower band for selecting satisfied duration and step size is needed than the other ANN models. However, when the duration and step size are selected, performance may be superior to the other two.

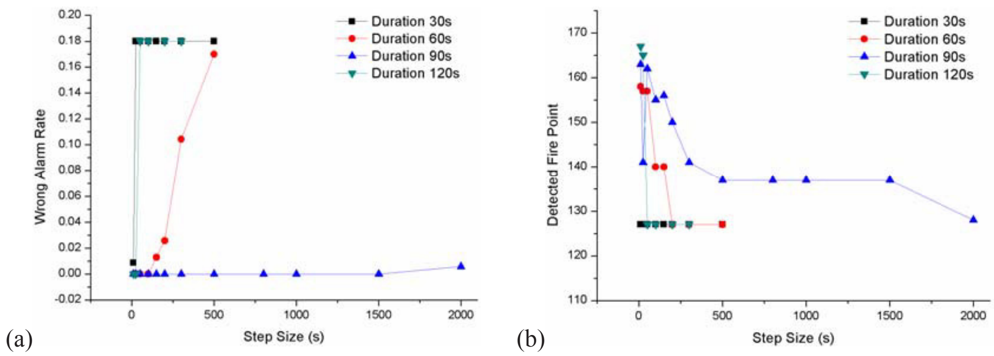

Fig 13 PNN Fire Detection Performance under Various Durations and Step Sizes for (a) Wrong Alarm Rate (b) Detected Fire Point

4. Conclusions

Dynamic moving observation window is an important measure in multisensor based fire detection. Selection of suitable observation window duration and step size is accordingly significant for feature extraction in multisensor fire detection technology. This will generate appropriate inputs for ANN models to differentiate fire from non-fire state. Three prevalent ANN models, namely BP, RBF and PNN, are selected to investigate influences of observation window duration and step size.

It is found that observation window duration of 90s is highly recommended for all three ANN models from the research results. The according step size can vary from 100s to more than 1000s. Performance of surprising low wrong alarm rate of PNN model with a duration of 90s is highlighted in the research.

Observation window duration is thus the primary component to be considered in design an ANN fire detection model. With optimized duration, effect of changes of step size is limited to a slight range. If duration is beyond the optimization range, step size can still affect the fire detection results to a large extent.

Various ANN models all display outstanding performances in multisensor fire detection. However, for calculation efficiency and precise fire detection results, synthetic performances of PNN are superior to the other two in a wide range of duration and step size parameters in this research. Further research may still be needed to incorporate more experimental results to investigate effectiveness of the optimized parameters found in this research.

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