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A multidimensional adaptive algorithm for fire detection

Abstract

Information about the normal state of a watched object is collected simultaneously with the operation of a fire detection system. The signals of sensors are rescaled to approach the normal distribution and a method of statistical inference based on the Fisher-Snedecor distribution and the χ^2-distribution is applied. The significance levels are justified using computer simulation. The algorithm is able to discriminate between normal and anomalous situations. The discrimination between fire and other anomalous situations is a subject of an additional dedicated algorithm not considered in the paper.

Introduction

An algorithm of fire detection depends on the tasks of the system and the set of sensors. A multisensor monitoring system acquiring versatile information about the watched object is assumed in the study. Fire detection is one of the many tasks of a universal monitoring system as discussed in [1]. Concretely, an orbital space station has been considered as a watched object when studying the problem. The main task of the system was the detection of fire precursors and an additional task was the detection of accidental emissions of air pollutants.

The set of scalar signals of all sensors is considered as a multidimensional vector signal. It is possible to analyse the multidimensional signal by single components and use traditional algorithms of fire detection developed for single-sensor systems. In this case the information about correlations between the signals of individual sensors is lost. An effect obtained by consideration of correlation between two sensors is shown by Siebel [2]. Another example is presented in the paper [3] where the analysis of temperature fields available only in multisensor systems is discussed.

The number of correlated component pairs in a multidimensional system is rising with the square of the number of components. Substantial analysis of the correlation is a complicated problem even in case of a two-sensor system as demonstrated by Siebel [2]. Only formal analysis is feasible when the number of sensors is big. A solution is possible when following the statistical approach. Complications embarrassing the usage of classical algorithms of statistical inference in fire detection are well known. The information about statistical distribution of signal in a fire situation is limited and not well formalised.

The processes are not stationary as it is expected in the theory of classical methods of mathematical statistics, and the distributions are far from the normal distribution expected in most of the parametric methods.

The methodology of this study is using an approximate model assembled from elements of traditional parametric mathematical statistics. The presumptions of strict statistical procedures are not satisfied and the significance levels are deformed. Therefore, the algorithms can be applied in practice only after some empirical adjustment of the critical levels of the test statistics that was made using computer simulation and Monte Carlo method.

The procedure of fire detection is spliced into three stages:

1) rescaling of sensor signals,
2) identification of anomalous situations,
3) discrimination between various possible anomalous situations.

The first and the third stage are system-specific and they are not particularised in the paper.

Null-hypothesis

The signal of a sensor consists of variations induced by random changes of environmental situation. In a proper time interval the variations can be modelled by a stationary stochastic process. A multidimensional signal is described by a multivariate statistical distribution.

When setting up hypotheses, the general statistical distribution of the signal is decomposed to a set of partial distributions corresponding to different situations like the normal situation, the fire situation, the equipment overheating situation, the dust situation, the cigarette smoking situation, the gas leak situation etc. A hypothesis is stating that the observed signal belongs to a determined subset of partial distributions. In the traditional theory of statistical inference two hypotheses called the null-hypothesis and the alternative hypothesis are considered. These two hypotheses are excluding each other. Therefore, the full set of situations should be spliced into two subsets. If a hypothesis consists of one partial distribution, it is called simple. Otherwise, it is called composite. Traditional methods of statistical inference are assuming a simple null hypothesis. Some prior information is required about the partial statistical distribution corresponding to the null-hypothesis. The alternative hypothesis can be composite and no prior information about the member distributions is required.

Two methods of setting up the hypotheses are used in fire detection. In the first method, the fire situation is assumed as a null-hypothesis and non-fire situation joining all

the other situations is assumed as an alternative. Some prior information about the fire situation is required and the task of the preparatory research is to get required information about the statistical distribution of the signal in fire situation. In the second method, the normal situation is assumed as a null-hypothesis and the anomalous situation joining all the other situations is assumed as an alternative. In this case prior information about the statistical distribution of the signal in the normal situation is necessary.

The first method yields a wanted answer about the existence or non-existence of fire. The second method can directly pronounce only the anomaly of the situation but cannot differ between the situations of fire, anomalous dust, etc. Therefore, the second method can be considered only as a first step in the fire identification. After an anomaly is detected, the signal should be additionally analysed to discriminate between various possible anomalous situations.

The anomalous situations are seldom and most of the time a multisensor system is acquiring information about the normal situation [4]. Thus, the statistical distribution of the signal in normal situation can be studied and adjusted step by step when the system is running. It allows to reach maximum possible performance without special research before installation of the system. When the normal situation is not stationary but the full time interval can be spliced into quasi-stationary subintervals, the system is able to accommodate itself to changing conditions. In case of the first method, the statistical information about the fire situation cannot be collected simultaneously with running the system in working conditions. Therefore, only the second method is capable of self-learning and adaptation to the real conditions when the system is in operation.

In case of the second method, a warning message is issued in any anomalous situation. An additional analysis is required to discriminate the kind of anomaly. A standard mathematical technique called the discrimination analysis can be used for solving the problem.

The role of the intersensor cross-correlation

A simple example below shows the advantages of the multivariate approach. Consider the signals of two temperature sensors located not far from each other. A sample of 100 measurements is depicted in Figure 1. In case of the single-dimensional approach, a warning message is issued when a measurement falls out of the dashed rectangle. In the multidimensional approach, the discrimination region is the narrow ellipse and the measurement P is identified as anomalous. However, when the correlation is ignored, the discrimination region is depicted by the wide ellipse and the measurement P does not bring about a warning message. Disregarding the correlation causes the loss of informa-

tion measured by logarithm of the ratio of areas of discrimination regions. The loss of information is proportional to the number of sensors. Therefore, disregarding the correlation is especially harmful in big multisensor measurement systems.

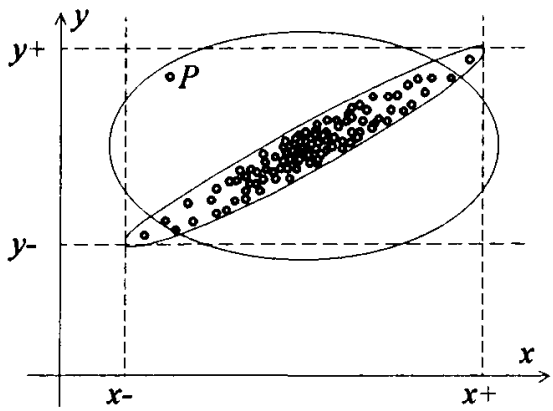

Figure 1. Random distribution of signals of two spaced temperature sensors x and y in a normal situation. x-, x+, y- and y+ are individual critical limits of signal components.

In a first glance, the loss of information seems to result only in the decrease of the sensitivity of the system. However, the sensitivity and probability of false alarms are bound each with other. The system manager is free to choose low sensitivity accompanied by a low probability of false alarms or a high sensitivity accompanied by a high probability of false alarms. It follows that in case of conservation of the sensitivity the probability of false alarms will essentially increase when the correlation is neglected.

The significance of correlation in a sophisticated fire detection system is demonstrated in the paper [5].

Parametric or non-parametric method

Parametric methods of statistical inference are based on knowledge about statistical distribution of the signal. A special feature of fire alarm systems is a very low permitted probability of false alarms. Therefore, the shape of the wings of the distribution function is essential. Popular parametric methods of statistical inference are elaborated for normal or Gauss distribution. The distribution of a fire detector signal is usually far from the normal distribution. As a rule, an attempt of a straightforward use of the common receipts of statistical inference testing the fire situation null-hypothesis results in an

unexpected high rate of false alarms. Therefore, dedicated algorithms considering the peculiarities of a task of fire detection [6] are more successful in practice

An alternative is a statistical approach based on non-parametric methods. However, the straightforward application of standard non-parametric algorithms yields the specific problems discussed by Siebel [2]. Siebel has proposed a special method for application of the Kendall test to the fire sensor signal mixing the signal with a random noise of given amplitude. The efficiency of the algorithm is depending on the amplitude of the added noise. The amplitude has a role that is similar to the discrimination level in parametric methods of statistical inference.

Non-parametric methods do not give an alarm after a single spike of the signal. This feature has pros and contras. Pro is that a pulse perturbation of a signal will not follow in a false alarm. Contra is that issuing of an instantaneous alarm is blocked even in such extreme situations as a sudden jump of temperature up to 400 C.

Rescaling of signals

The shape of the distribution function of a signal can be controlled by a non-linear transformation of the signal scale. Classical methods of single-dimensional statistical inference based on the normal distribution are correct when a variable is rescaled in a proper way. The components of a multidimensional signal can be individually rescaled, in order to obtain a normal distribution for every component. This does not guarantee that the multidimensional signal is distributed according to the Gauss law. Thus the normalising rescaling applied individually to the single components of a multidimensional signal should be considered as an approximate method.

The rescaling and application of parametric tests based on the normal distribution is possible when original distribution is estimated on a basis of a very big amount of measurements. This is possible only when studying the distribution of a signal in the normal situation. Therefore, only the normal situation can be the subject of a null-hypothesis when trying to use the parametric methods by means of the rescaling technique.

Controlled rescaling is based on parametrisation of transformation functions. Concrete methods are sensor-specific and are not discussed in the present paper.

Measurement and variables

The number of sensors in the system is saved in a variable N_s. Signals of sensors are measured in cycles with a period of T_0. The rough signal y_i of the sensor number i is rescaled immediately after the measurement to a normally distributed variable $x_i = f_i(y_i)$.

Instead of direct storing of the signal measured in the preceding cycle x_i^-, the drifts are saved as additional components of the vector x: $x_{Ns+i} = x_i - x_i^-$. The composite signal is an N-dimensional vector $x = \{x_1,...,x_N\}$ where $N = 2N_s$. The older values of the signal are not preserved and are not analysed. The reason of the simplification is the need to keep the amount of computations in a reasonable level.

The exactness of statistical estimates depends on the length of uninterrupted measurement series. Due to the possible failures or reinstallation of some sensors in the working system, the number of measurements can be specific for various sensors and it is denoted by n_i. As a rule, when the measurements are started, some prior information about the possible value of the signal is available. Thus, a conditional value n_i^o is determined so that the exactness of estimates in case of n_i^o measurements would be the same as the exactness of the prior estimates. The initial state of the system with a prior information is $n_i = n_i^o$.

When a failure of a sensor is identified, the value of n_i is set to zero. The value $n_i = 0$ is a mark of a void sensor during the statistical analysis. The void sensors are ignored and the number N is reduced by two for every void sensor during data processing. After a sensor is repaired, the value n_i is set to n_i^o and the value of N is restored.

Statistical inference

The basic parameters of a normally distributed stochastic vector x are the mean value m and the covariance matrix $C = \langle(x - m)(x - m)^T\rangle$. The deviation of the value x from the mean value is measured by the square of the Mahalanobis distance

$$d^2 = (x - m)^T C^{-1}(x - m).$$

The statistics d^2 is distributed according to the χ^2-law with N degrees of freedom. It gives a possibility to make decisions according to the value of d^2.

In a real situation, the values of m and C are unknown and are replaced by the estimates calculated according to n independent measurements. If the Mahalanobis distance is computed using the estimates of m and C, the statistics

$$f = \frac{(n-N)d^2}{N(n+1)}$$

is distributed according to the Fisher-Snedecor law $F(N,n\text{-}N)$ [7]. Unfortunately, the Fisher test cannot be applied in a straightforward way because:

1) the sequential measurements are correlated,
2) the size of the sample can be specific for different components of the vector x.

An exact solution of the problem is unknown. Therefore, an approximate method is proposed. The algorithm designed according to the approximate method must be checked using computer simulation and Monte Carlo method, and the percentage points of the test statistics should be adjusted to fit the results of the computing experiment.

The approximate method is based on the ratio

$$\xi = \frac{N(n+1)}{n-N} \frac{F_F^{-1}(N,n-N)}{F_{\chi^2}^{-1}(N)} ,$$

where F_F^{-1} is the critical value of the F-distribution and $F_{\chi^2}^{-1}$ is the critical value of the χ^2-distribution on the required significance level. The ratio ξ is interpreted as a coefficient of increase in the critical level of d^2 when the χ^2-test is replaced by the F-test. It allows to replace the F-test by χ^2-test when all the components of $(\boldsymbol{x} - \boldsymbol{m})$ are simultaneously multiplied by the coefficient $\sqrt{\xi}$. The χ^2-test for $(\boldsymbol{x} - \boldsymbol{m})\sqrt{\xi}$ yields the same result as the F-test for original deviations. The advantage of the modified procedure is that the components of the vector $(\boldsymbol{x} - \boldsymbol{m})$ can be corrected individually accounting the individual size of the component sample when computing the values of ξ_i.

Another approximate method is used to account the autocorrelation. The correlation functions of x_i are fitted by the function $\exp(-\Delta/c_i)$ where Δ is the time interval expressed as a number of cycles, and c_i is a coefficient estimated according to the real measurements. The number of degrees of freedom in the χ^2-test is determined by the effective number of independent measurements $n'_i = n / c_i$ in the approximate method.

Adaptation

Adaptation of the inference algorithm is carried out by a continuous study of the statistical behaviour of the signal in a normal situation and a correction of the information presented by the vector $\boldsymbol{m}$ and matrix C after every measurement. The time window of the measurements used by the estimation of $\boldsymbol{m}$ and C is restricted, the old information is forgotten step by step and the algorithm is continuously adopted for the actual situation.

The exponential time window used when estimating $\boldsymbol{m}$ and C is achieved accounting the measurements with weights $\exp(-\Delta t/n_0T_0)$, where n_0T_0 is an efficient width of the window. The exponential window is economical in computing as there is no need to store the time series. Sequential correction of the averages is made according to the algorithm:

if $n<n_0$ then $n := n + 1$;

$\boldsymbol{m} := \boldsymbol{m} + (\boldsymbol{x} - \boldsymbol{m})/n$;

When estimating the covariation matrix, the exponential window is provided in a similar way.

Matrix C must be corrected after every measurement. The number of arithmetic operations required for refreshing the covariation matrix is in the order of n^2. This amount of calculations is within a power of a microprocessor. However, the inverse matrix is required in the statistical test. The number of operations inverting a matrix is in the order of n^3 and that can cause technical problems. A solution is the recursive refreshing of the inverse matrix using the Dwyer-Waugh method [8]. A specific algorithm [9] enables to find all the required quantities according in an economic way. The running information is saved in the number of valid measurements n, average m, standard deviation s, and the inverse matrix A of the correlation matrix. The computation to be performed in one measurement cycle is:

```
for i := 1 to N do begin
        nn := n_i + 1;
        xx := x_i - m_i;
        m_i := m_i + xx / nn;
        s_i := sqrt (n_i * s_i^2 + xx^2) / nn;
        x_i := xx / s_i;
        if nn <= n_0 then n_i := nn;
end:
d^2 = 0;
for i := 1 to N do begin
        vv := 0;
        for j := 1 to N do vv := vv + A_ij * x_j;
        d^2 = d^2 + vv * x_i;
        v_i := vv;
end;
for i := 1 to N do for j := 1 to N do begin
        if n_j < n_i then nn := n_j else nn := n_i;
        A_ij := (nn / (nn - 1)) * (A_ij - v_i * v_j / ((nn - 1) + d^2));
end;
```

The value of the wanted statistics d^2 is received automatically in the process of the computation above.

Conclusions

Performance of a multisensor fire detection system can be improved considering correlations between the signals and signal drifts of various sensors. Statistical behaviour of the multidimensional signal must be known when making decisions about the status of the watched object. Collecting multidimensional information is a time-consuming process Behaviour of the system is typically changing in time and collecting the information must be carried out simultaneously with the operation of a real system. The statistical model can be built only for the normal situation because the anomalous situations are not available for collecting information in a working system. The process of fire detection is spliced into three stages: rescaling of the signal components, statistical inference, and discrimination between various anomalous situations. The first and the third stage are system-specific, and a universal algorithm can be composed for the second stage. A computationally economic algorithm is proposed to collect the information simultaneously with estimating the Mahalanobis distance between the multidimensional signals in actual and average normal situations. The estimate of Mahalanobis distance is used as test statistics in a modified χ^2-test.

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