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Fault detection of aircraft based on support vector domain description☆

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ABSTRACT

To realize intelligent fault detection of aircraft lacking fault samples, a novel fault detection algorithm for aircraft based on Support Vector Domain Description (SVDD) is proposed. The Genetic Algorithm (GA), threshold scaling factor, rapid anomaly detection, modifying kernel function and SVDD model boundary based on equal loss are introduced to the fault detection algorithm. The empirical analyses show that the method has good fault detection ability. The classification accuracy is improved by 5.52% after using the GA. The fault detection time of the SVDD algorithm is improved by 0.4 seconds on average when compared to the red line shutdown system. The accurate classification rate is enhanced by 0.0225, and the number of support vectors is reduced by 1 after adopting the modified kernel function. The fault detection algorithm in this paper provides novel intelligent fault detection technology for aircraft.

1. Introduction

Support Vector Domain Description (SVDD) is a one-class classification method recently developed by David M.J. Tax et al. The core idea is to treat the object as a whole and construct a hypersphere in the eigenspace so that the complete object or the majority of it is included in the hypersphere. An object falling into a different class is completely excluded or minimally included in the hypersphere. Points within the hypersphere are classified as the target class, and points outside the hypersphere are classified as the non-target class. Thus, the aim of separating the two classes can be achieved [1–3].

The hypersphere has two features, the center a and radius R, as shown in Fig. 1. By minimizing the radius, the area circumscribed by the hypersphere is also minimized, while the amount of training data included is maximized. Under most scenarios, it might not be feasible to separate the target class and non-target class completely. There are overlaps between the classes during the mapping onto the eigenspace. To address these overlaps, the slack variable ε_i was added to allow some points to appear on the wrong side of the boundary. Therefore, the first problem that needs to be solved for fault detection of aircraft based on SVDD is minimizing the radius of the hypersphere:

$$\min F(R, a, \varepsilon) = R^2 + C\sum_i \varepsilon_i \tag{1}$$

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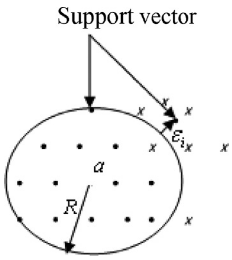

Fig. 1. Schematic diagram of the hypersphere.

The constrained condition is:

$$(x_i - a)(x_i - a)^T \le R^2 + \varepsilon_i, \varepsilon_i \ge 0, \forall i \tag{2}$$

where C is a penalty on the misclassified sample.

Applying Lagrange multipliers can transform the problem into a minimized target function L:

$$\begin{aligned} &L(R, a, \alpha_i, \gamma_i, \varepsilon_i) = R^2 + C\sum_i \varepsilon_i - \sum_i \alpha_i(R^2 + \varepsilon_i - \|x_i - a\|^2) - \sum_i \gamma_i\varepsilon_i \\ &s.t.\ 0 \le \alpha_i \le C,\ \sum_i \alpha_i = 1 \end{aligned} \tag{3}$$

where Lagrange multipliers $\alpha_i \ge 0$, $\gamma_i \ge 0$. Partial derivatives for R, a, ε_i were obtained to give the following optimized problem:

$$\begin{aligned} &\max_{\alpha_i} L(\alpha_i) = \sum_i \alpha_i(x_i \cdot x_i) - \sum_{i,j} \alpha_i\alpha_j(x_i \cdot x_j) \\ &s.t.\ 0 \le \alpha_i \le C,\ \sum_i \alpha_i = 1 \end{aligned} \tag{4}$$

Finally, the fault detection problem in aircraft based on SVDD is transformed into the following test function (where z is the sample to be fault detected):

$$\|z - a\|^2 = (z \cdot z) - 2\sum_i \alpha_i(z \cdot x_i) + \sum_{i,j} \alpha_i\alpha_j(x_j \cdot x_i) \le R^2 \tag{5}$$

If the above test function is to be applied in discriminant decisions, the radius of the hypersphere must be calculated during training:

$$R^2 = (x_k \cdot x_k) - 2\sum_i \alpha_i(x_k \cdot x_i) + \sum_{i,j} \alpha_i\alpha_j(x_i \cdot x_j) \tag{6}$$

where x_k is any support vector from the set of support vectors that satisfy $a_k < C$.

However, most real-world problems are non-linearly distributed. According to the kernel method, a non-linear mapping φ is first adopted to map data into a high-dimensional eigenspace, and linear classification is then performed in the high-dimensional eigenspace. After mapping the data back into the original space, the data become a non-linear classification in the input space [4,5]. To avoid complex calculations in high-dimensional space, the kernel function $K(x_i, x_j)$ can be used to replace the inner product calculation $\langle\varphi(x_i), \varphi(x_j)\rangle$ of the high-dimensional eigenspace.

After introducing the kernel function, the target optimized function becomes:

$$\max_{\alpha_i} L(\alpha_i) = \sum_i \alpha_i K(x_i \cdot x_i) - \sum_{i,j} \alpha_i\alpha_j K(x_i \cdot x_j) \tag{7}$$

which is constrained by: $0 \le \alpha_i \le C$, $\sum_i \alpha_i = 1$.

The formula expressing the corresponding R^2 and test function can be written as:

$$R^2 = K(x_k \cdot x_k) - 2\sum_i \alpha_i K(x_k \cdot x_i) + \sum_{i,j} \alpha_i\alpha_j K(x_i \cdot x_j) \tag{8}$$

For the new sample Z, the detection discriminant function is (9), where $a = \sum_{i=1}^{l} \alpha_i\phi(x_i)$.

$$f(z) = \|\phi(z) - a\|^2 = K(z \cdot z) - 2\sum_i \alpha_i K(z \cdot x_i) + \sum_{i,j} \alpha_i\alpha_j K(x_i \cdot x_j) \le R^2 \tag{9}$$

The rest of this paper is organized as follows. The implementation of the detection method based on SVDD is explained clearly, mainly including the optimization of the SVDD kernel parameters based on the Genetic Algorithm (GA) and the introduction of the threshold scaling factor, the rapid anomaly detection algorithm, a method of modifying the kernel function and the SVDD model boundary. The conclusions of this paper are listed at the end.