STEEL PLATE FAULT DIAGNOSIS BASED ON AN INTEGRATION OF ONE-AGAINST-ONE STRATEGY AND SUPPORT VECTOR MACHINES

PHÁT HIỆN LỖI CỦA THÉP TẤM DỰA TRÊN SỰ KẾT HỢP CỦA CHIẾN LƯỢC ONE-AGAINST-ONE VÀ MÁY HỌC VÉC TƠ HỖ TRỢ

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Abstract - Fault diagnosis has been a critical issue in industrial production over years. An effective fault diagnosis system enhances the quality of manufacturing and reduces the cost of product testing. This paper proposes an integration of one-against-one (OAO) strategy and support vector machines (SVM) to diagnose multiple faults of steel plates. The OAO is adopted to address multi-classification tasks in the binary SVM (*i.e*, OAO-SVMs). The performance of the proposed model is compared with that of optimization algorithm-based SVM. Analytical results indicate that the OAO-SVM outperforms other comparative models in fault diagnosis with an accuracy up to 86.357%. The findings of this paper, therefore, show a potential combination of an OAO strategy and an SVM in sorting common faults of steel plates in particular and industrial products in general.

Key words - Fault diagnosis; one-against-one; support vector machines; steel plates; classification accuracy.

Tóm tắt - Phát hiện lỗi đã trở thành một vấn đề quan trọng đối với ngành công nghiệp sản xuất trong những năm qua. Một hệ thống phát hiện lỗi hiệu quả sẽ thúc đẩy chất lượng sản xuất và giảm chi phí kiểm tra sản phẩm. Bài báo này đề xuất một sự kết hợp của chiến lược one-against-one (OAO) và máy học véc-tơ hỗ trợ (SVM) để phát hiện các lỗi của thép tấm. Chiến lược OAO được sử dụng để hỗ trợ SVMs thực hiện đa phân lớp (đó là, OAO-SVM). Sự thể hiện của mô hình đề xuất được so sánh với mô hình SVM dựa trên các thuật toán tối ưu. Kết quả phân tích chỉ ra rằng mô hình OAO-SVM vượt trội các mô hình khác trong việc phát hiện lỗi với độ chính xác tới 86,357% kết quả của bài báo này, vì vậy, thể hiện sự kết hợp tiềm năng của chiến lược OAO và mô hình SVM trong việc phân loại các lỗi phổ biến của thép tấm nói riêng và những sản phẩm công nghiệp nói chung.

Từ khóa - Phát hiện lỗi; one-against-one; máy học véc-tơ hỗ trợ; thép tấm; độ chính xác trong phân loại.

1. Introduction

Materials and manufacturing are generally recognized as the main cost components of products. It is very essential to diagnose faults in manufacturing systems [1]. A fault is defined as an unacceptable difference of at least one characteristic property or attribute of a system from an acceptable usual typical performance. Fault diagnosis is aimed to determine the location and occurrence time of possible faults on the basis of accessible data and knowledge about the performance of diagnosed processes [2]. An effective fault diagnosis method not only lowers maintenance cost and unexpected waste, but also improves production efficiency and quality level of products. Moreover, further treatments such as recycling are also based on an accurate faults diagnosis [3, 4].

Faults diagnosis in manufacturing process has been a subject of interest for many researchers. Traditionally, manual inspections were used to discover or infer potential causes of a particular fault. This method is time consuming, low accuracy, and need a lot of manpower. In recent years, intelligent fault detection techniques have been employed to address the problems of faults diagnosis [5-7]. These techniques that are derived from artificial intelligence and data mining models should be simple and efficient [8].

Neural network-based methods have been widely applied in fault prediction [5, 6]. For instance, Lo et al. (2002) [6] integrated the genetic algorithm (GA) and qualitative bond graphs (QBG) to diagnose faults on a newly constructed floating disc system. The GA is utilized to find a set of fault candidates while the QBG is adopted as the formal modeling scheme which provides a unified approach to model different energy domain subsystems together. Lau et al. (2010) [5] used an adaptive neuro-fuzzy inference system for online fault diagnosis of a gas-phase polypropylene production process. Testing results showed that the proposed system was more effective in diagnosing multiple faults compared to conventional multivariate statistical approaches.

Recently, support vector machines (SVM) [9] have been a powerful technique in solving pattern recognition problems. By applying the structural risk minimization principle, SVM has a better generalization ability than neural networks. It is time-saving in computation when solving high-dimension problems, which cannot be achieved by artificial neural networks, logistic regression, decision tree, etc [10]. The SVM was originally designed for the solution of binary classification problems. However, many problems in real worlds need to be solved in multi-classification (for instance, faults diagnosis of steel plates). This obstacle could be addressed by the one-against-one (OAO) strategy which modifies the binary SVM to handle multiclass tasks.

This study, therefore, proposes a multi-classification method of the SVM, namely OAO-SVM to predict multiple faults of steel plates. This dataset is selected as a case study for its important role in raw material industry manufactures [10].

The rest of this paper is organized as follows. Section 2 elucidates the SVM, OAO, and the classification accuracy evaluation methods. The collection and preprocess of steel plates dataset, and analytical results are mentioned in Section 3. Finally, conclusions is given in Section 4.

2. Methodology

2.1. Support vector machines for binary classification

Introduced by Vapnik et al. (1995) [9], the SVMs executed a classification by constructing an N-dimensional hyperplane that optimally separates the data into binary categories. The best hyperplane for an SVMs means the one with the largest margin between the two classes. Margin means the maximal width of the slab parallel to the hyperplane that has no interior data points. Figure 1 shows a basic structure of the binary support vector machines.

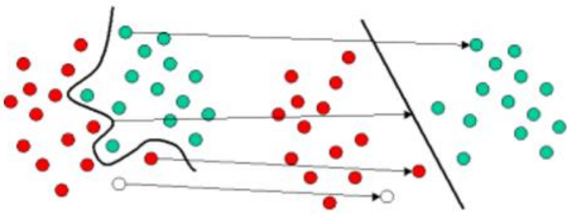

Figure 1. *Architecture of binary support vector machines*

The formulation of an SVMs classifier can be initiated using two following assumptions.

$$\vec{w} \bullet \vec{x_+} + b \geq 1 \quad \text{if } x = +1 \tag{1}$$

$$\vec{w} \bullet \vec{x_-} + b \leq 1 \quad \text{if } x = -1 \tag{2}$$

where $\vec{w}$ denotes an SVMs margin vector; $\vec{x_+}$ and $\vec{x_-}$ denote an SVMs positive class vector and an SVMs negative class vector, respectively; b denotes an SVMs bias term; y_i indicates the class to which the sample $\vec{x}$ belongs; and $\bullet$ denotes dot products. The assumptions (1) and (2) are the constraints for minimizing Eq. (3) to maximize the margins between various categories.

$$\min_{\vec{w}} = \frac{1}{2} \| \vec{w} \|^2 \tag{3}$$

The results of the Lagrange multiplier equation are used to optimize Eq. (3) as follows.

$$L(\alpha_i) = \frac{1}{2} \| \vec{w} \|^2 - \sum_{i=1}^{N} \alpha_i (y_i (\vec{w_i} \bullet \vec{x_i} + b) - 1) \tag{4}$$

where α_i denotes a Lagrange slack variable. When the Lagrange equation is solved using quadratic programming (QP) solvers, the α_i, $\vec{w_i}$, b values can be obtained. These values can be used to determine a unique maximal margin solution.

The decision boundary lies in the middle of two class distributions. However, a different problem arises when the data point of a class lies in the distribution area of another class. This problem can be solved by applying an SVM classifier to another space, and a kernel-mapping function can facilitate this process. The inner product can be defined via using a kernel according to the Mercer condition. To classify an unknown $\vec{x}$, a kernel function $K(\vec{x_i}, \vec{x})$ must be computed against each support vector ($\vec{x_i}$).

Kernel mapping functions are powerful because they enable SVMs models to execute classifications without considering the dimensions of sample space, even for classes demonstrating highly complex boundary. In spite of available numerous kernel mapping functions, a few kernel functions have been demonstrated to operate effectively in a wide variety of applications. The radial basis function (RBF) kernel is commonly used because of its high efficient performance [11]. Eq. (5) shows the RBF kernel equation.

$$K(\vec{x}, \vec{x_i}) = \exp\left(- \frac{\| \vec{x} - \vec{x_i} \|^2}{2\sigma^2} \right) \tag{5}$$

where σ is the kernel function parameter.

2.2. One-against-one strategy

One-against-One (OAO) and One-against-Rest (OAR) are the most widely used decomposition strategies. However, OAO [12] is one of the most effective available decomposition strategies [13]. Therefore, the OAO algorithm was used for decomposition herein. The OAO scheme divides an original problem into as many binary problems as possible pairs of classes. Typically, the OAO method constructs $k(k - 1)/2$ classifiers [14], where k is the number of classes. All classifiers are combined to yield the final result. Different methods can be used to combine the obtained classifiers for the OAO scheme whereas the most common method is a simple voting method [15].

2.3. Classification accuracy evaluation

Accuracy can be defined as the degree of uncertainty in a measurement with respect to an absolute standard. The predictive accuracy of a classification algorithm is calculated as follows.

$$Accuracy = \frac{tp + tn}{tp + fp + tn + fn} \tag{6}$$

The true positive (tp) values (number of correctly recognized class examples) and true negative (tn) values (number of correctly recognized examples that do not belong to the class) represent accurate classifications. The false positive (fp) value (number of examples that are either incorrectly assigned to a class or false negative (fn) value (number of examples that are not assigned to a class) refers to erroneous classifications.

3. Data preparation and analytical results

3.1. Data preparation

The steel plate faults dataset used in the study comes from the UC Irvine Machine Learning Repository (UCI). In this dataset, faults in steel plates are classified into 7 types, which includes Pastry, Zscratch, Kscratch, Stains, Dirtiness, Bumps and Other. The dataset includes 1941 instances, which have been labeled by different fault types and 27 independent variables, which are used as input data.

To prevent confusion in multi-class classification, Tian et.al (2015) eliminated faults of class 7 because that class did not refer to a particular kind of fault [10]. Furthermore, to improve predictive accuracy, they used the recursive feature elimination (RFE) algorithm to reduce the number of dimensions of the multi-class classification. Accordingly, a modified steel plate fault dataset (1268 samples) with 20 independent attributes and six types of fault were adopted. Therefore, the proposed OAO-SVM applied the modified data to obtain a fair of comparison. Table 1 presents the inputs and profile of categorical labels for data concerning faults in steel plates.

Table 1. *Statistical input and profile of categorical labels for the steel plate faults diagnosis data*

Rank	Number	Parameter
		Input
1	20	Edges Y Index
2	21	Outside Global index
3	25	Orientation Index
4	19	Edges X Index
5	12	Type of Steel_A300
6	26	Luminosity Index
7	17	Square Index
8	13	Type of Steel_A400
9	11	Length of Conveyer
10	9	Minimum of Luminosity
11	2	X Maximum
12	1	X Minimum
13	27	Sigmoid of Areas
14	15	Edges Index
15	16	Empty Index
16	10	Maximum of Luminosity
17	22	Log of Areas
18	24	Log Y Index
19	23	Log X Index
20	14	Steel Plate Thickness
		Output -Type of fault
	1	Pastry (Class 1)
	2	ZScratch (Class 2)
	3	KScratch (Class 3)
	4	Stains (Class 4)
	5	Dirtiness (Class 5)
	6	Bumps (Class 6)

3.2. Analytical results

The performance of the OAO-SVM model is evaluated in terms of accuracy which is the most commonly used index. High values of accuracy indicate favorable performance and vice versa. Table 2 compares the predictive performances obtained by the proposed model and several empirical models [10] when applied to the steel fault dataset.

Table 2. *Accuracy comparison of empirical models and the proposed model*

Empirical models reported in primary work	Accuracy (%)	Improved accuracy by OAO-SVM (%)
GS-SVM [10]	77.8	14.586
GA-SVM [10]	78.0	14.366
PSO-SVM [10]	79.6	12.610
OAO-SVM	86.357	-

In the study [10], three optimizing algorithms - grid search (GS), genetic algorithm (GA) and particle swarm optimization (PSO) – were respectively used to optimize the performance of SVM. The PSO-SVM obtained the higher classification ability (with an accuracy of 79.6%) compared to that obtained by the GS-SVM and the PSO-SVM (with the accuracy of 77.8% and 78.0%, respectively). Meanwhile, the proposed OAO-SVM model yields a higher accuracy of 86.357%. Table 2 also shows the percentage improvement achieved by the proposed model when using experimental data. The classification accuracy obtained by the proposed model is 12.61-14.58% lower than values reported for empirical models. The sorting accuracy of the empirical models and the proposed model are further compared in Figure 2.

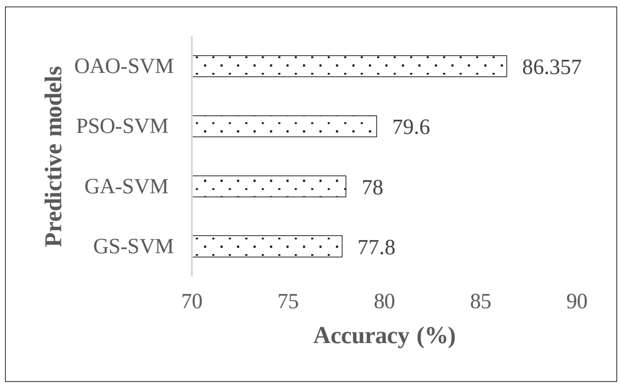

Figure 2. *Comparison of models in terms of accuracy*

4. Conclusions

This paper investigates the effectiveness of a useful model that integrates an OAO scheme and an SVM to improve its predictive accuracy in classifying steel plate fault diagnosis. To verify the applicability and efficiency, the predictive performance of the OAO-SVM model is compared with that of other prior studies with respect to accuracy. The proposed model exhibites a higher predictive accuracy than experimental models. Therefore, the proposed model can be used as a potential decision-making tool in diagnosing multiple faults of steel plates.

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