Application of Information-Geometric Support Vector Machine on Fault Diagnosis of Hydraulic Pump

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Abstract. The growing demand for the safety and reliability in industries triggers the development of condition monitoring and fault diagnosis technologies. Hydraulic pump is the critical part of a hydraulic system. The diagnosis of hydraulic pump is very crucial for reliability. This paper presents a method based on information-geometric support vector machine (IG-SVM), which is employed for fault diagnosis of hydraulic pump. The IG-SVM, which uses information geometry to modify SVM, improves the performance in a data-dependent way. To diagnose faults of hydraulic pump, a residual error generator is designed based on the IG-SVM. This residual error generator is firstly trained using data from normal state. Then, it can be used for fault clustering by analysis of the residual error. Its feasibility and efficiency has also been validated via a plunger pump test-bed.

1. Introduction

As processes and machinery become more and more complex, fault detection and diagnosis are emerging as the main task of a monitoring system and have an effective role for the safe operation and long life of systems. Condition monitoring is important for increasing machinery availability, improving manufacturing process productivity and reliability [1].

Hydraulic pump is a key component which varies the volume of fluid delivered to constant system pressure. If a fault detection scheme can be developed that gives an early warning of component failures, then repairs or replacements can take place at the earliest or most convenient time with the minimum loss of productivity [2]. So, diagnosis of hydraulic pump is necessary. However, hydraulic pump is complex and in a very high degree of coupling [3]. Considering the complexity and the severe working conditions, data-driven fault detection method is usually applies to its online fault diagnosis. By now, a lot of data-driven methods have been proposed, such as: wavelet decomposition [4], neural networks (ANNs) [5, 6], fuzzy logic, kernel principal component analysis [7], as well as D-S evidence theory [8].

Support vector machine (SVM), as a data-driven method, has been widely applied. Compared with ANNs, SVM overcomes many detects, such as over-fitting, local convergence. Additionally, SVM has advantages over ANNs, in terms of robustness and prevention of Curse of Dimensionality, etc. It has been applied in many fields, such as pattern recognition and fault diagnosis [1].

Despite the excellent applicability, the performance of SVM largely depends on the kernel [9, 10]. Mostly, the kernel functions are chosen by experience. However, unsuitably chosen kernel functions may lead to significantly poor performance [11]. By now, there seems to be no systematic way of choosing appropriate kernel functions [12]. It is reported that choosing a kernel corresponds to a smoothness assumption of the discriminant function of the classifier. In case when we have some prior knowledge, we can utilize them to choose a kernel [13]. However, in practice, the prior knowledge is usually unknown. Therefore, it is important to optimize the kernel in a data-dependent way. Here, an information-geometric method is employed in this study. By analyzing the structure of the Riemannian geometry induced in the input space by the kernel, the SVM can be modified in a data-dependent way and the information-geometric SVM (IG-SVM) can be obtained.

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In this paper, a residual error generator based the IG-SVM is designed to detect several types of failures of hydraulic pump with one-step prediction of chaotic time series. The feasibility and efficiency of this method is validated via a plunger pump test-bed.

2. Methodology

2.1. Modified SVM using information geometry

The SVM, proposed by Vapnik, aims at minimizing an upper bound of the generalization error through maximizing the margin between the separating hyperplane and the data. Suppose a pattern classifier, which uses a hyperplane to separate two classes of patterns based on given examples $D=\{(x_1,y_1),...,(x_i,y_i)\}$, where x is a vector in the input space $S=R^d$, $y\in\{-1,1\}$ is class label and $i=1,...,l$. A nonlinear SVM maps the input data x into a high dimensional feature space $F=R^n$ (n may be infinite) by using a nonlinear mapping $\phi(x)$. Detailed explanation about the basic concepts of SVM theory can be found in reference [11].

To modify SVM kernel using information geometry, it is necessary to analyze the geometrical structure induced in the input space by a kernel as follows [14].

The mapping $\phi(x)$ defines an embedding of S into S as a curved submanifold. When F is a Euclidean or Hilbert space, a Riemannian metric is thereby induced in the space S, where the length of a small line element dx in S is defined by the length in the larger space F.

Denote by z the mapped pattern of x in the feature space, i.e., $z=\phi(x)$. A small vector dx is mapped to

$$dz=\nabla\phi(x)dx=\sum_i\frac{\partial}{\partial x_i}\phi(x)dx_i \tag{1}$$

where

$$\nabla\phi(x)=\left(\frac{\partial}{\partial x_i}\phi(x)\right) \tag{2}$$

The squared length of $dz=(dz_\alpha)$ is written in the quadratic form as

$$|dz|=\sum_\alpha(dz_\alpha)^2=\sum_{i,j}g_{ij}(x)dx_idx_j \tag{3}$$

where

$$g_{ij}(x)=\left(\frac{\partial}{\partial x_i}\phi(x)\right)\left(\frac{\partial}{\partial x_j}\phi(x)\right) \tag{4}$$

The dot denoting the summation over index α of ϕ. The $n\times n$ positive-definite matrix $G(x)=(g_{ij}(x))$ is the Riemannian metric tensor induced in S. It shows that the metric is directly derived from the kernel.

Based on the above analysis, in order to improve the forecasting precision in regression problems, special nonlinear map ϕ, can be constructed such that $g_{ij}(x)$ is reduced around the neighboring areas of hyperplane: $|y-f(x)-b|=\xi$, which is contrary to the method of Amari in classification problems. This idea can be implemented by a conformal transformation of kernel,

$$\tilde{K}(x,x') = c(x)c(x')K(x,x') \tag{5}$$

with a properly positive scalar function $c(x)$. $\tilde{K}(x,x')$ is called a conformal transformation of a kernel by factor. The nonlinear mapping $\phi(x)$ can be regarded as being modified to $\tilde{\phi}(x) = c(x)\phi(x)$, which satisfies the Mercer positivity condition.

Therefore, if we choose the function $c(x)$ in a way such that its value is large when x is close to the boundary and small otherwise, we can realize the idea of enlarging the spatial resolution around the boundary [9]. Taking the above analysis into consideration, $c(x)$ can be chosen as:

$$c(x) = \frac{1}{m}\sum_{i=1}^{m}\exp\left(\frac{-\|x-o_i\|^2}{\tau^2}\right) \tag{6}$$

where the parameter m, o_i, τ are the number of the partitioning points, the center and the width of the ith partition, respectively. Out of the circles, the value of $c(x)$ is very small, so is its derivative [13]. Therefore, this function satisfies the aforementioned requirement and can be used to modify SVM in a data-dependent way.

2.2. Residual error generator

Residual error generator can be designed for fault diagnosis based on IG-SVM prediction process. The structure is shown in figure 1.

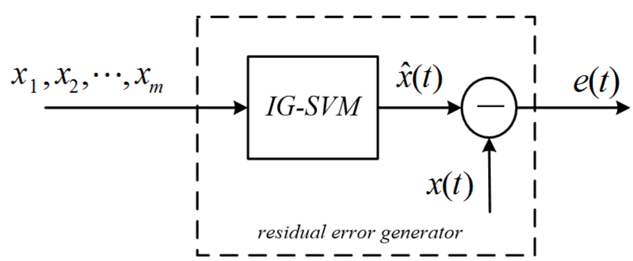

Figure 1. Structure of Residual Error Generator based on IG-SVM.

Where, $x(t)$ is the time series which can be observed of actual system, IG-SVM is the residual error generator trained by the data from normal state, $\tilde{x}(t)$ is the one-step prediction value of IG-SVM, and $e(t)$ is the output of residual error generator.

The diagnostic decision is obtained based on the following rule:

$r_{eval} > J_{th}$ → Fault state detected

$r_{eval} \le J_{th}$ → Normal state

Where, r_{eval} is the mean absolute value of residual error signal, and J_{th} is the threshold and can be determined by experience.

3. Experimental results

In this section, a test rig of SCY Hydraulic plunger pump, was tested and analyzed to verify the presented method. In the experiment, two common types of fault in plunger pump were set respectively: wear fault between swash plate and slipper and wear fault of valve plate. Under three kinds of states, including normal state, as shown in table 1, vibration signal was respectively acquired from the end face of plunger pump, with a stabilized motor speed at 5280r/min, and a sampling rate of 1000Hz.

Table 1. Hydraulic pump's datasets.

Data	State
Data1	Normal condition
Data2	Wear fault between swash plate and slipper
Data3	Wear fault of valve plate

In this case, 200 points of time series data from normal state were used. The first 100 samples were employed for training of SVMs, and the last 100 samples for testing and determination of the threshold of fault diagnosis. The number of input nodes of SVM was 6. After training and testing, prediction model of normal state can be determined. Figure 2 shows the result using one-step iterative prediction based IG-SVM.

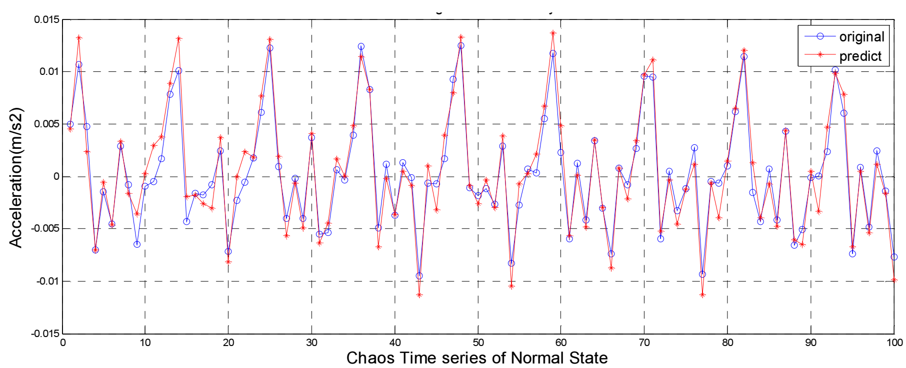

Figure 2. One-step iterative predicted result of data from normal state.

3.1. Residual error of normal state

With the residual error generator, the residual error of normal data can be gained. As aforementioned r_{eval} the mean absolute value of residual error will be used for fault clustering. Figure 3 shows the absolute value of residual error of normal state.

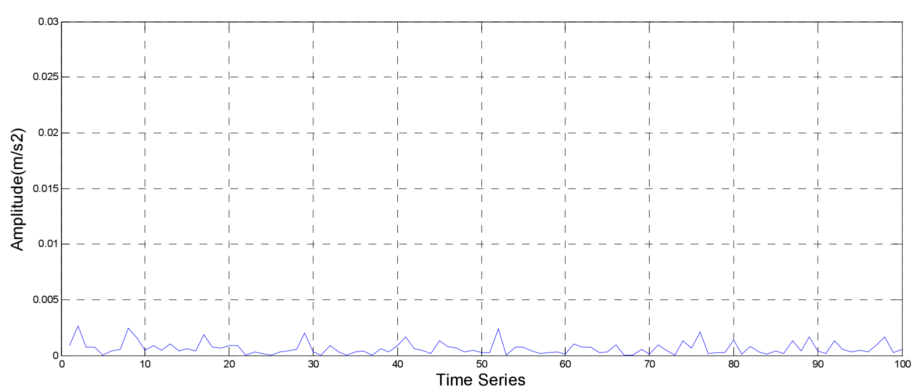

Figure 3. Absolute value of residual error of normal state.

3.2. Residual error of wear fault between swash plate and slipper

Here, 100 points of time series data from the vibration signal with wear fault between swash plate and slipper were used via the residual error generator. Figure 4 shows the absolute value of residual error of wear fault between swash plate and slipper.

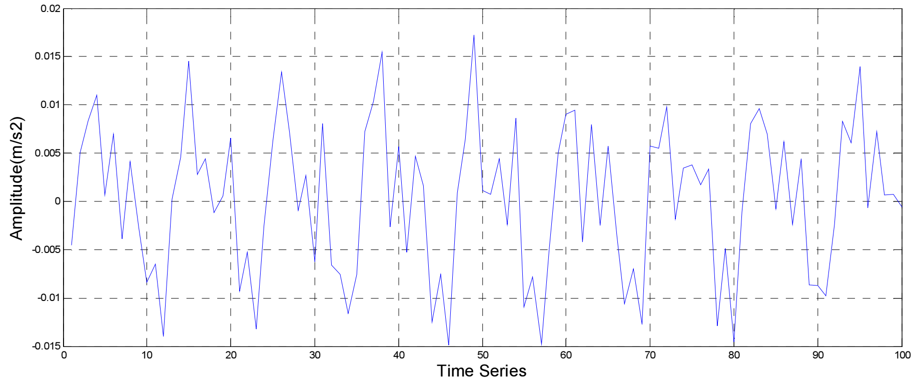

Figure 4. Absolute value of residual error of wear fault between swash plate and slipper.

3.3. Residual error of wear fault of valve plate

100 points of time series data from the vibration signal of hydraulic pump with wear fault of valve plate were used for fault detection. Figure 5 shows the absolute value of residual error.

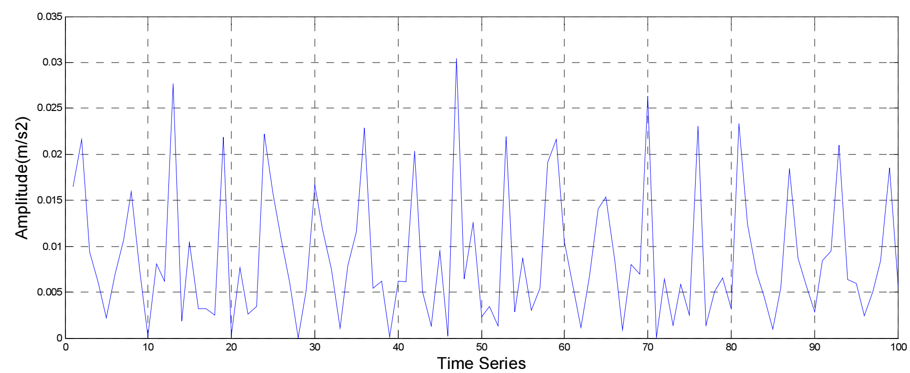

Figure 5. Absolute value of residual error of wear fault of valve plate.

3.3.1. Discussion

As aforementioned, with the residual error generator based on IG-SVM, the residual error series were calculated respectively. The results show a 100% success rate in correct detection and isolation of hydraulic pump faults. This implies that the IG-SVM residual error generator can diagnose faults of hydraulic pump successfully.

4. Conclusion

The strong nonlinearity features in the vibration signals of hydraulic pump bring difficulties for fault diagnosis. In this paper, a method based on IG-SVM is presented to solve this problem. The IG-SVM improves the performance of SVM in a data-dependent way. This advantage is utilized to construct a residual error generator for fault diagnosis. Additional works are needed to further validate the method in wider applications. Meanwhile, how to determine the number of input nodes of SVM is also an issue that should be recognized.

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