Journal of Applied Sciences

ISSN 1812-5654

Journal of Applied Sciences 13 (16): 3209-3214, 2013
ISSN 1812-5654 / DOI: 10.3923/jas.2013.3209.3214

Fault Diagnosis of Rotating Shaft Systems Based on Wavelet Entropy and GA-SVM

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Abstract: A new fault diagnosis method for rotating shaft system of marine diesel engine is proposed in this paper. The proposed method is an integrated application of wavelet packet, Shannon entropy, SVM (Support Vector Machine) and GA (Genetic Algorithm) theory. Based on the simulation platform for marine diesel engine shafting, wavelet packet decomposition and strong fault-tolerant Shannon entropy are used to compute the feature vectors of vibration signals, which are then served as the input vectors of SVM; GA is used to optimize the parameters of SVM when it is trained to achieve higher veracity. The study result shows that WPS-GS can get higher reliability and veracity than the conventional SVM and BP neural network, which means the provided method is more suitable for the condition monitoring and fault diagnosis of rotating shaft system.

Key words: Fault diagnosis, rotating shaft system, wavelet packet, shannon entropy, genetic algorithm, support vector machine

INTRODUCTION

The shaft systems as an important part of marine diesel engine, once a fault occurs, not only affects the normal operation of the equipment and may also cause serious accidents. Therefore, shaft systems fault diagnosis is particularly important. The task of the shaft system fault diagnosis is to extract the fault characteristic and establish the pattern of fault identification.

Extraction of the fault characteristic information: The frequency domain analysis of Fast Fourier Transform, due to the low resolution ratio, it is not suitable for the treatment of non-stationary signals (Bowen and Zhang, 2006); the time-frequency domain analysis of Short Time Fourier Transform (Yu *et al*., 2003), Wavelet Transform may loss the information which is contain in the high-frequency section (Wang *et al*., 2005). And Wavelet Packet Transform can divide the frequency band into multi-level and further decompose the high frequency part (Cao and Zhang, 2008). Shannon entropy extracted by Wavelet Packet can reflect high time-frequency resolution ratio (He *et al*., 2005).

Recognition of the fault pattern: SVM (Support Vector Machine) is based on the statistical theory; SVM can obtain fine classification and generalization ability in the case of small sample size and has better generalization capability than Artificial Neural Network (Jack and Nandi, 2002). The GA (Genetic Algorithm) has the implicit parallelism, better ability of global optimization and adaptively to adjust the parameters of SVM to the optimal value, so SVM can show the best performance (Zhang *et al*., 2010). In the past two years, GA-SVM has been applied to fault recognition, but has not been found in the fault diagnosis of ship shafting.

This study uses GA to optimize the parameters of SVM, takes the fault diagnosis of the main engine for an example and then extracts Shannon entropy as input samples by the means of Wavelet Packet, finally sets up a kind of diagnosis model based on wavelet packet, Shannon entropy, GA and SVM, namely: WPS-GS model.

THE PRINCIPLE OF WPS-GS MODEL

Wavelet packet and shannon entropy: Wavelet Packet analysis is based on multi-resolution framework, similar to the Discrete Wavelet Transform, the main difference is that the Discrete Wavelet Transform only decompose the scale space, while the Wavelet Packet Transform further decompose the high frequency section which has no details and according to the characteristics of the signal, Wavelet Packet Transform can adaptively select the appreciate frequency band, thereby increase the resolution ratio in the domain of time-frequency, so Wavelet Packet is more suitable for processing non-stationary signals (Wu and Liu, 2009).

Entropy is a quantity which can be used to measure the chaotic degree of a system. Greater the entropy is, the system is more chaos and less information; smaller the entropy is, the system is more orderly and more information. Entropy is widely used in a variety of areas, especially in the field of signal. The Shannon entropy combined with the wavelet packet as follows (Avci and Akpolat, 2006):

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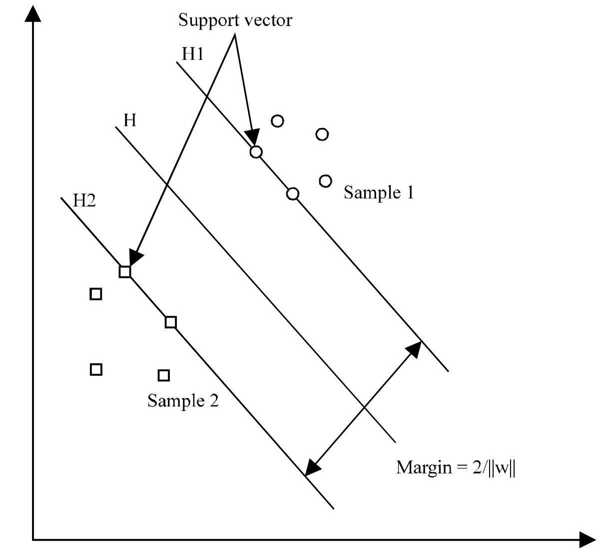

Fig. 1: Optical hyperplane

$$En = \sum_{j}^{16} d_{j,k}^{2n} \log d_{j,k}^{2n}$$

$d_{j,k}^{2n}$ is the coefficient of wavelet packet decomposition, n = 1, 2, 3..., 15, usually E0 contains a large amount of noise signal, so WPS-GS do not take it as signal characteristics, we use the rest of the En to construct feature vectors of the vibration signal and then regard feature vectors as input vectors.

Genetic algorithms: Genetic Algorithms was proposed by Professor Holland of the University of Michigan in 1969, summarized by Goldberg (1989) and then formatted a new global optimization search algorithm. When using the genetic algorithms to solve the problem, each of the possible solution is encoded into a "chromosome", namely individual, several individuals constitute the population (all possible solutions), then through the fitness function, we eliminate individuals with low fitness and choose individuals with high fitness to do the genetic operation. These individuals through crossover and mutation operator are combined to generate the next generation of new population. Therefore, Genetic Algorithms can be viewed as a process of evolution which is composed of feasible solutions (Zhou and Ling, 2010).

Support vector machine: SVM is based on the principle of structural risk minimization; the basic idea is illustrated as Fig. 1. In Fig. 1, the solid and hollow dots represent two kinds of samples. H is the classification line; H1, H2, respectively represent classifications which are nearest to the classification line and parallel to it. The distance between H1 and H2 is class interval (margin) and regard the samples on H1 and H2 as support vector (Li *et al*., 2003; Saleh *et al*., 2011).

Extended to nonlinear sample set, through nonlinear mapping ?, mapping the vector X to a high dimensional feature space and then construct the optimal separating hyperplane in the high dimensional feature space. The classification decision function is:

$$y = \text{sgn}[\sum_{x_i \in sv} \alpha_i y_i K(x_i, x) + b]$$

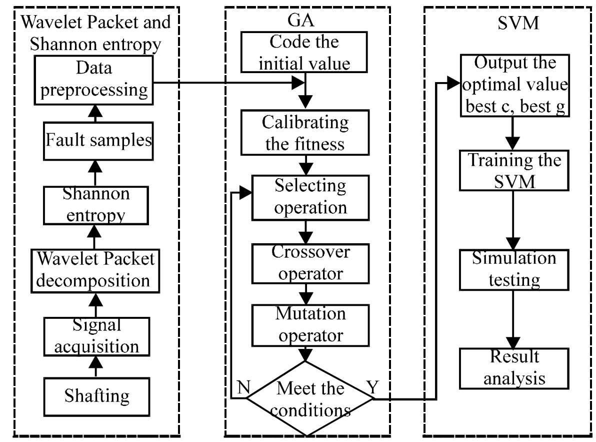

Fig. 2: The basic flow chart of WPS-GS

WPS-GS model: First, using Wavelet Packet to get faulty samples and then using GA to optimize penalty parameter c and kernel function parameter g of the SVM. Finally, verifying the generalization ability through the test set. The basic process is shown in Fig. 2.

EXPERIMENTAL ANALYSIS

The designing of the experiment platform: The structure of the platform is modeled similar as the ships of the Hansen line. Mainly include five parts: power excitation (dashed box 1), torque transfer (dashed box 2), load regulation (dashed box 3), the base (dashed box 4) and samples collection (dashed box 5), as shown in Fig. 3. The total length of the shaft is 1200 mm, the diameter is 25 mm, divided the shaft into the intermediate shaft and stern shaft, the length ratio is 13:7. The torsional oscillation is mainly reflected on the intermediate shaft. The end of the stern shaft is connected to a three-blade propeller which is in a water tank. We can regulate the level of the water to adjust the load. In order to simulate the vibration state,

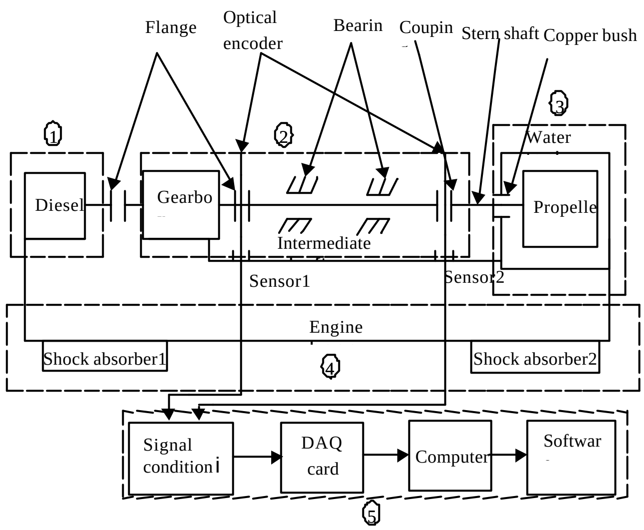

Fig. 3: Platform structure schematic

Table 1: Fault simulation

Operating conditions	Fault simulation measures
Misalignmet of the shafting	Add pads at the edge of the intermediate shaft and stern shaft coupling
Gear slipping	Loose friction plate of the gearbox
Rotor eccentricity	Add eccentric block on the blade

the platform is installed on a base which is equipped with vibration springs at the bottom (Feng *et al*., 2002). Fault simulation case is shown in Table 1.

Extraction of the feature vectors: The signals of the photoelectric sensor first processed by a front-end processor and then send the signals to PCI6220 data acquisition card, do dual-channel synchronous acquisition by data acquisition card under the control of software. Because the data acquisition belongs to different interval sampling, this is not conducive to analyze the data, therefore, we resampling the data through cubic spline interpolation to realize uniform sampling (Hu *et al*., 2008). That is to say, suspend the collection after 21 sec and then interpolate the collected data each 10 m sec, this determines the sampling frequency is 100 Hz and each channel has 2048 sampling points.

Using the wavelet packet decomposition to decompose and reconstruct the data and then extract the energy spectrum- Shannon entropy as feature vector. Eventually, we get 40 groups of samples, including 24 training samples and 16 test samples, as showed in Table 2 and 3. Since the outputs of the network corresponding to four states of the bearing, these four states are encoded as: Normal (1), Misalignment of the shafting (2), Gear slipping (3), Rotor eccentricity (4) and regard the four codes as the ideal outputs of SVM and GA.

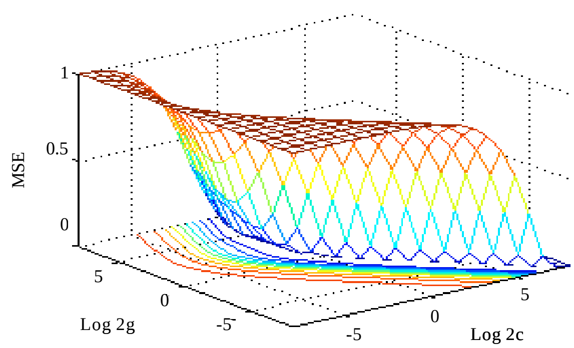

Fig. 4: The result of SVR parameters selection (contour map)

GA optimized parameters of the SVM: In order to avoid overfitting and underfitting, we adopt the idea of cross-validation and grid-search to search the best parameter c and g. As an efficient heuristic algorithm, GA does not have to traverse all parameters within the grid when find the global optimal solution. Parameters of the GA are set as follows: The maximum number of population 20; the maximum number of iteration 100; the crossover rate 0.4; mutation rate 0.001; the range of parameter c[0.1 100]; the range of parameter g [0.01 1000]. Based on the matlab 2007, we conclude that Bestc = 9.1896, Bestg = 9.1896, Cvmse = 0.020464, as showed in Fig. 4 and 5.

Table 2: Training samplings

Operating conditions	Feature vector A	B	C	D	E	F	G	H
Normal (1)	0.0449	0.3209	0.1314	0.1461	0.0411	0.1093	0.0978	0.1085
Normal (1)	0.0767	0.3274	0.1330	0.1974	0.0237	0.0738	0.1035	0.0644
Normal (1)	0.0337	0.3371	0.1185	0.1215	0.0377	0.1294	0.1001	0.1219
Normal (1)	0.0338	0.3918	0.1196	0.1560	0.0530	0.0953	0.0731	0.0772
Normal (1)	0.0465	0.4357	0.1119	0.1772	0.0542	0.0681	0.0581	0.0484
Normal (1)	0.0903	0.2601	0.1423	0.1753	0.0497	0.0636	0.1548	0.0639
Misalignment of the shafting (2)	0.2426	0.1615	0.1241	0.0970	0.0499	0.0999	0.1084	0.1167
Misalignment of the shafting (2)	0.2797	0.1671	0.1061	0.0681	0.0452	0.1380	0.0987	0.0972
Misalignment of the shafting (2)	0.2616	0.1604	0.1327	0.0943	0.0530	0.0994	0.1316	0.0670
Misalignment of the shafting (2)	0.2684	0.2808	0.1064	0.1039	0.0369	0.0701	0.0619	0.0716
Misalignment of the shafting (2)	0.2353	0.2554	0.0980	0.1228	0.0293	0.0908	0.0730	0.0953
Misalignment of the shafting (2)	0.2919	0.1098	0.1476	0.0787	0.0403	0.0915	0.1763	0.0640
Gear slipping (3)	0.4996	0.1851	0.0725	0.0899	0.0348	0.0429	0.0391	0.0360
Gear slipping (3)	0.5307	0.1459	0.0694	0.0883	0.0339	0.0428	0.0459	0.0430
Gear slipping (3)	0.5213	0.2017	0.0630	0.0773	0.0300	0.0354	0.0331	0.0383
Gear slipping (3)	0.4196	0.2287	0.0930	0.1104	0.0318	0.0439	0.0357	0.0369
Gear slipping (3)	0.4879	0.1769	0.0826	0.0978	0.0355	0.0434	0.0374	0.0384
Gear slipping (3)	0.4709	0.1791	0.0870	0.1267	0.0311	0.0388	0.0318	0.0346
Rotor eccentricity (4)	0.7420	0.1035	0.0304	0.0489	0.0207	0.0243	0.0237	0.0245
Rotor eccentricity (4)	0.7668	0.0961	0.0247	0.0450	0.0117	0.0182	0.0191	0.0184
Rotor eccentricity (4)	0.7279	0.1061	0.0303	0.0532	0.0153	0.0238	0.0221	0.0214
Rotor eccentricity (4)	0.6934	0.1015	0.0370	0.0470	0.0250	0.0292	0.0336	0.0334
Rotor eccentricity (4)	0.6940	0.1031	0.0367	0.0472	0.0186	0.0410	0.0351	0.0244
Rotor eccentricity (4)	0.6612	0.0656	0.0599	0.0445	0.0258	0.0401	0.0759	0.0269

Table 3: Test samplings

Operating conditions	Feature vector A	B	C	D	E	F	G	H
Normal (1)	0.0542	0.3943	0.1315	0.1476	0.0515	0.0844	0.0733	0.0633
Normal (1)	0.0386	0.4240	0.1266	0.1413	0.0543	0.0825	0.0744	0.0583
Normal (1)	0.0585	0.3245	0.1627	0.1186	0.0412	0.1098	0.0931	0.0917
Normal (1)	0.0687	0.2375	0.1553	0.1719	0.0405	0.0819	0.1718	0.0724
Misalignment of the shafting (2)	0.2195	0.1764	0.1510	0.0923	0.0468	0.0760	0.1796	0.0584
Misalignment of the shafting (2)	0.2204	0.1333	0.1492	0.0834	0.0527	0.1111	0.1744	0.0754
Misalignment of the shafting (2)	0.2431	0.1930	0.1163	0.1421	0.0397	0.0735	0.1271	0.0652
Misalignment of the shafting (2)	0.2904	0.1801	0.1031	0.1410	0.0416	0.0703	0.1145	0.0588
Gear slipping (3)	0.5202	0.1756	0.0775	0.0876	0.0358	0.0361	0.0336	0.0337
Gear slipping (3)	0.4325	0.2389	0.0745	0.0925	0.0360	0.0424	0.0424	0.0407
Gear slipping (3)	0.4404	0.2618	0.0885	0.0925	0.0293	0.0290	0.0299	0.0285
Gear slipping (3)	0.4386	0.2208	0.0764	0.1128	0.0325	0.0449	0.0344	0.0397
Rotor eccentricity (4)	0.6612	0.1010	0.0372	0.0525	0.0251	0.0540	0.0391	0.0299
Rotor eccentricity (4)	0.7735	0.0883	0.0194	0.0409	0.0178	0.0280	0.0166	0.0155
Rotor eccentricity (4)	0.6859	0.0670	0.0595	0.0418	0.0212	0.0356	0.0639	0.0251
Rotor eccentricity (4)	0.6643	0.0612	0.0704	0.0399	0.0223	0.0349	0.0797	0.0273

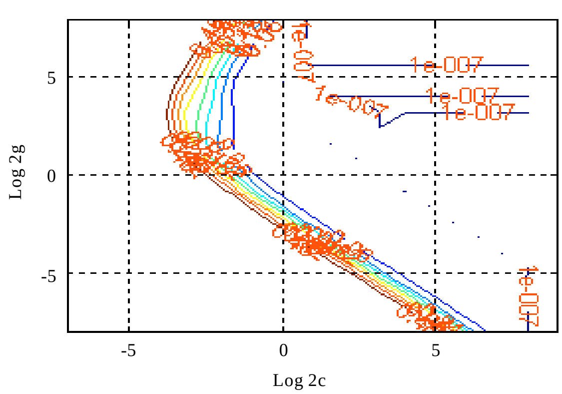

Fig. 5: The result of SVR parameters selection (3D view)

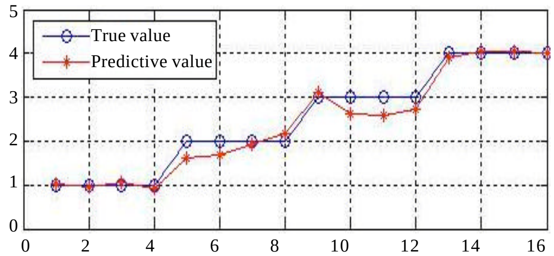

Fig. 6: Prediction map based on WPS-GS

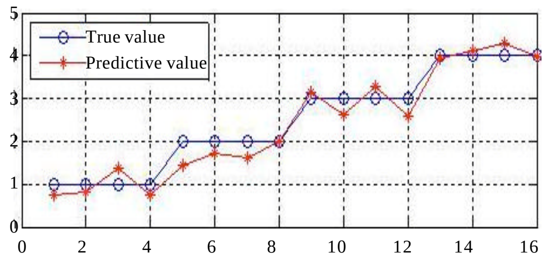

Fig. 7: Prediction map based on SVM

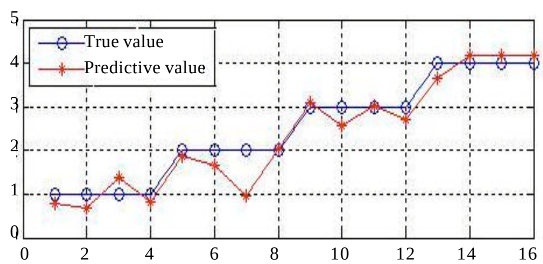

Fig. 8: Prediction map based on BP

Analysis of the results: Establishing the SVM network structure based on the RBF kernel function, Best c and Best g. Training and modeling the training samples and then predicts the 16 test samples. Results: Mean squared error = 0.0421786, Squared correlation coefficient = 0.978468, the predicted results are shown in Fig. 6 and 7 uses the method of SVM without GA, compared with Fig. 6, it is able to identify the fault but the overall vibration is too large. Figure 8 uses the method of BP, because of overfitting, the seventh sample recognition error.

CONCLUSION

Under the judgmental criterion of identification, WPS-GS model can effectively identify the faults of the shafting. WPS-GS model can not only overcome the shortcomings of the BP-NN, such as the dependence of the network initial value, easy to fall into local minima but also has better performance on robustness and accuracy compared with traditional SVM. The further work of this paper is to apply the method of WPS-GS to dynamic monitoring and diagnosis of the shafting fault.

ACKNOWLEDGMENT

This study is supported by Natural Science Foundation of China (No. 61071198), Scientific Research Fund of Zhejiang Provincial Education Department (No. Y201224770), Natural Science Foundation of Zhejiang Province (No. Y1110161), Natural Science Foundation of Ningbo (No.2012A610019) , Innovative Science Research Team Foundation of Ningbo (No.2011B81002).

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