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On-line Condition Monitoring and Remote Fault Diagnosis for Marine Diesel Engines Using Tribological Information

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Literature review indicates that a large amount of failures are caused by abnormal wear of the diesel engine components. It is therefore essential to monitor the engine condition using the tribological information. Although the wear debris analysis has been proven to be effective for condition monitoring and fault diagnosis (CMFD) of diesel engines, limited work has been done to address the remote on-line CMFD system in practice. To extend the oil monitoring technology into industrial application level, a new remote on-line fault diagnosis system for marine diesel engines has been proposed in this paper. The new system consists of an on-line tribological signal acquisition model in the ship, a remote feature extraction model and a fault diagnosis model in the laboratory center. Nine wear characteristics were extracted to detect the engine faults, including the surface roughness of wear particles, oil moisture and viscosity, and index of particle covered area (IPCA), etc. In order to select a relative best feature for the on-line fault detection, the interaction information based feature selection method was employed to determine the suitable indicator. This study has found that the IPCA is the best feature among other eight features to on-line respond the engine condition changes. The diagnosis results show that the new system offers satisfactory on-line fault diagnosis ability and is effective for the diesel engine fault diagnosis in practice.

1. Introduction

The operation reliability and safety is the most crucial issue for ships. However, due to harsh working environment, ship components are prone to damages and a crack in the hull or a fracture of the bent axle in the internal-combustion engine may cause serious accidents. The report of the Swedish Club Highlights on the main engine damage claims demonstrated that during 1998 to 2004 a total 482, 994, 204 dollars had been compensated for 1238 claims of ship damages. Table 1 shows the claim numbers and costs of the seven categories. This high incidence and cost of ship machinery damage should be reduced by proper damage prevention programme.

According to Swedish Club Highlights, the most frequent failure components are the main engine and auxiliary engine. It can be noticed that the claim numbers of the main engine and auxiliary engine account for 64% of the machinery claims. Another survey (Yan and Sun, 2003) indicated the faults caused by friction and wear account for 50% of the faults in marine diesel engines. Considering the diesel engine has been served in more than 90% of vessels (Lamaris and Hountalas, 2010), it is therefore crucial to monitor the condition of marine diesel engines from point of view of tribology to prevent malfunctions of machinery.

The oil monitoring technology has been proven to be efficient in tribological failure detection (Jones and Li, 2000; Yan, et al., 2005; Peng, et al., 2005; Peng and Kessissoglou, 2003; Yuan et al., 2005; Zhou and Yan, 2008). The use of the wear debris monitors and oil sample analysis can reveal the wear characteristics associated with the operation states of a diesel engine (Ozogan, Khalil and Katsoulakos, 1989). However, traditional off-line laboratory oil analysis delays the decision making and hence its application in practice is limited (Lunt, 2011). With an increasing demand for real-time execution of oil analysis, the on-line oil monitoring sensors and detection systems attract great interest of both academic and industrial researchers(Markova et al., 2010; Kauffman and Ameye, 2002; Mohammadi et al., 2010; Villaret al., 2010;

Wu et al., 2009; Yan et al., 2011). Therefore, for practice use the outcomes of the on-line oil monitoring and fault diagnosis system should be evaluated in marine diesel engines.

Table 1. The claim numbers and costs of the seven categories [2].

Claims type	Number	Proportion of claim number	Total cost (USD)	Proportion of claim cost
Heavy weather	83	6.70%	25.040.827	5.18%
Contact	172	13.89%	41.037.341	8.50%
Collision	130	10.50%	129.829.551	26.88%
Grounding	133	10.74%	58.028.719	12.01%
Fire/Explosion	24	1.94%	36.932.101	7.65%
Machinery	558	42.07%	151.134.439	31.29%
Other	138	11.15%	40.991.227	8.49%
Total	1238	100%	482.994.204	100%

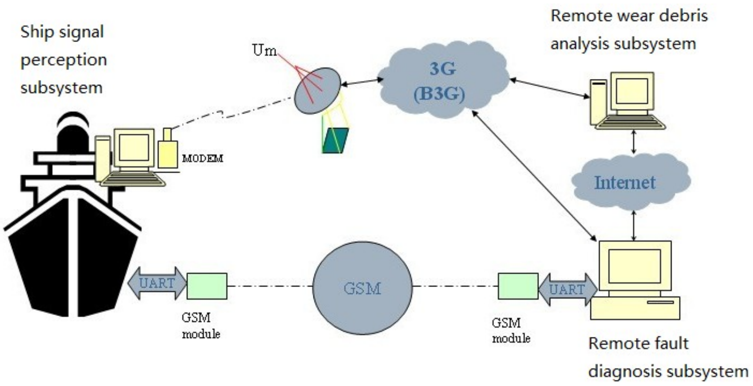


Figure 1: The sketch diagram of the proposed fault diagnosis for marine diesel engines.

This paper presents a new development of remote on-line fault diagnosis system for a series of real ships. It consists of a condition monitoring subsystem in the ship and a fault diagnosis subsystem in laboratory centre. The 3rd generation telecommunication (3G/B3G) wireless communication system has been used to connect the two subsystems. A microscopic image processing technique based on-line ferrographic monitor is adopted to analyze the wear debris characteristics of the engine oil, and an on-line moisture and viscosity detection sensor is used to monitor the lubricant condition. A feature selection method based on the Shannon mutual information is followed to rank the oil features.

2. Description of proposed remote on-line fault diagnosis system

2.1 Signal perception and fault feature extraction

The sketch diagram of the proposed fault diagnosis for marine diesel engines is shown in Figure 1. Two on-line sensors have been employed in the present diagnosis system. One is the on-line ferrographic sensor (Wu, Mao, Wang, Wu and Xie, 2009). The other is the on-line oil moisture and viscosity detection device (Yan, Sun, Yin, Li and Liu, 2011). The on-line ferrographic sensor uses the image processing technology to calculate the index of particle covered area (IPCA) and hence to count the numbers of the large wear particles (Wu, Mao, Wang, Wu and Xie, 2009), and the moisture and viscosity detection is realized by the use of the linear relationship between the oil moisture content and the color saturation.
To simplify the wear debris analysis, a remote knowledge service subsystem is developed to calculate the roughness and size of the wear particles. This subsystem has integrate a series of signal processing functions and provides remote image processing services for wear debris using the web service technique (Liu and Yan, 2010). The sensors firstly send the wear images to the wear debris subsystem by 3G/B3G.

2.2 Feature selection

After the feature extraction, the wear particle numbers and size, roughness, IPCA, oil moisture and viscosity, etc. are sent to the fault diagnosis subsystem for potential failure detection. Generally, these features are useful for the fault diagnosis of diesel engines. However, aiming to a fast respond to failures, it is crucial for the fault diagnosis subsystem to use one or two most informative features to monitor the machinery condition. For this purpose, the interaction information based feature selection criterion (Brown et al., 2012) is adopted to automatically identify the most meaningful features of the extracted variables in this work. The interaction information is a generalization of Shannon's mutual information to the case where multivariate (more than two variables) mutual information can be solved. The dependencies among multiple variables can be described as (Brown et al., 2012)

$$I(\{X_1, ..., X_m\}) = I(\{X_1, ..., X_{m-1}\} | X_m) - I(\{X_1, ..., X_{m-1}\}), \tag{1}$$

where, function denotes the interaction information among all variables, the term denotes the conditional mutual information and m denotes the numbers of total variables. If m = 2, then the interaction information reduces to Shannon's mutual information:

$$I(\{X_1, X_2\}) = I(X_1; X_2), \tag{2}$$

where, function denotes the Shannon's mutual information.
As for the feature selection issue, the information gain of each feature reflects its relevance or/and redundancy degree with regard to the class labels. Given a set of features and a target T, the interaction information based feature selection criterion can be expressed as (Brown, Pocock, Zhao and Luján, 2012)

$$J = I(F_m; T) - \sum_{i=1}^{m-1} [I(F_m; F_i) - I(F_m; F_i | T)] \tag{3}$$

It can be seen that the information gain of feature F_m is determined by its own mutual information, the correlations terms between itself and other features, and its class-conditional probability terms. This means that the most informative feature is a balance between these components (Brown et al., 2012): the relevance of the feature to the target, redundancy of the feature to its rivals, and class-conditional redundancy. More details about the interaction information based feature selection criterion can be found in Brown et al. (2012).

3. Experiments and results

In the experiment tests, the diesel engine has run for 100 hours. The on-line ferrographic sensor and oil moisture and viscosity detection device sampled the lubricant oil every 2 hours, and the lubricant oil was collected every 12 hours for the purpose of off-line oil analysis. A slight crack was seeded on a gear pump of the tested diesel engine. During the engine operation, the crack developed and broke down the gear pump in the late stage of the experiment.

3.1 Interaction information based feature selection

50 samples were collected from three stages of the diesel engine operation: the early testing stage where the engine could be regarded as working in normal condition, the middle stage where engine was in slight faulty condition, and the late stage where the gear pump was broken down. The contribution of each feature to the target is listed in table 2.
The relevance gain of the IPCA is 0.350, the largest value among the nine features. This tells us that the IPCA is most sensitive to the change of the engine operation state. Meanwhile, the viscosity shares the second most informative feature. Its relevance gain is 0.244, i.e. the second largest value, whilst its redundancy and conditional redundancy are equal to the values of the IPCA. This is mainly because that the crack has reduced the boundary lubrication of the gears and increased the metal-to-metal contact, and hence the metal wear particles have increased significantly. As a result, the oil viscosity has changed with the severity of the gear wear and reflected the operation state of the engine. On the other hand, the oil viscosity has used the variation of wear particles to assess the engine health condition. This is an indirect manner. However, the IPCA is a direct measurement on the change of the wear particles. So, the IPCA has been selected as the prior choice to detect engine faults in the remote on-line diagnosis system.

3.2 On-line fault diagnosis

Figure 2 shows the ferrographic images of the diesel engine using the on-line ferrographic sensor. The on-line IPCA monitoring results is shown in Figure 3. One can note that in Figure 2 the numbers and area of large wear particles increase gradually with the severity of the engine fault. Obvious large wear particles appear around 45 testing hours, and severe heavy-worn particles emerge during 65 to 100 testing hours. Meanwhile, it can be seen in Figure 3 that in the early stage of the testing the IPCA value maintains at a relative low lever while after 40 testing hours it increase rapidly. The average IPCA value is 367 from 50 to 100 testing hours and the maximum IPCA value reaches up to 450. These IPCA values are much larger than a normal value of 50. As a result, the abnormal operation state of the diesel engine has been detected effectively using the IPCA.

Table 2. The feature selection results.

Features / Terms	Number	Area	Diameter	Perimeter	Roughness	IPCA	Moisture	Wear type	Viscosity
Relevance	0.043	0.0669	0.074	0.076	0.205	0.350	0.185	0.189	0.244
Redundancy	0.293	0.123	0.276	0.195	0.312	0.168	0.378	0.391	0.168
Conditional redundancy	0.198	0.082	0.161	0.104	0.146	0.087	0.157	0.163	0.087

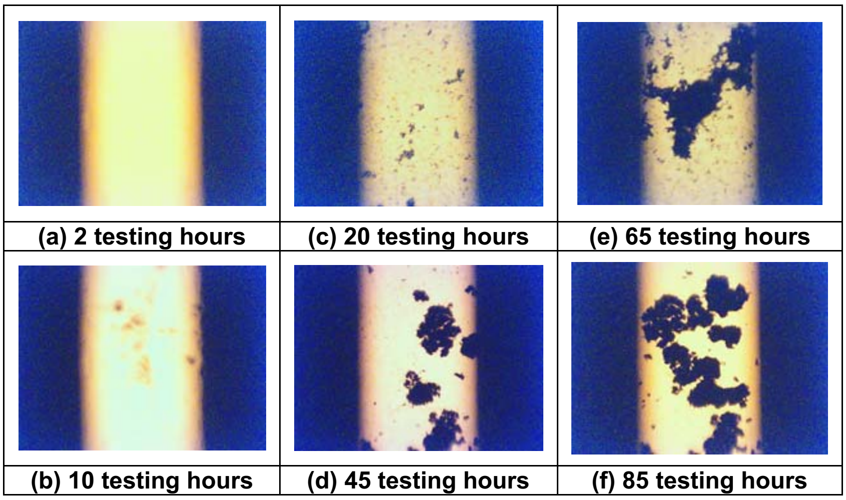


Figure 2: The ferrographic images of the diesel engine at different testing time.

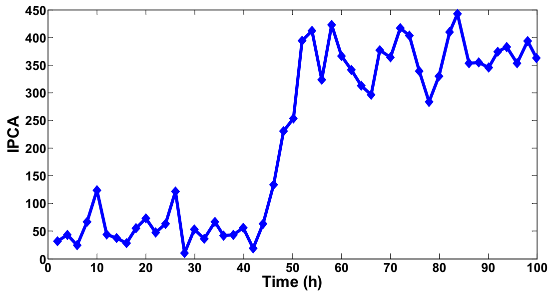


Figure 3: The curve of the index of particle covered area (IPCA).

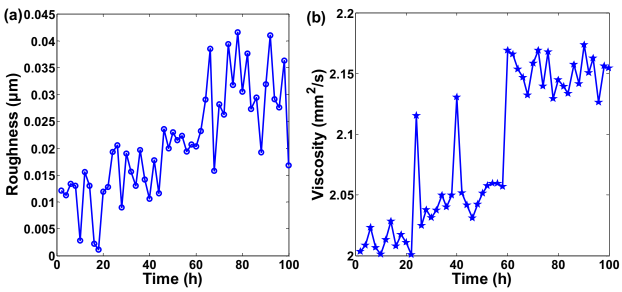
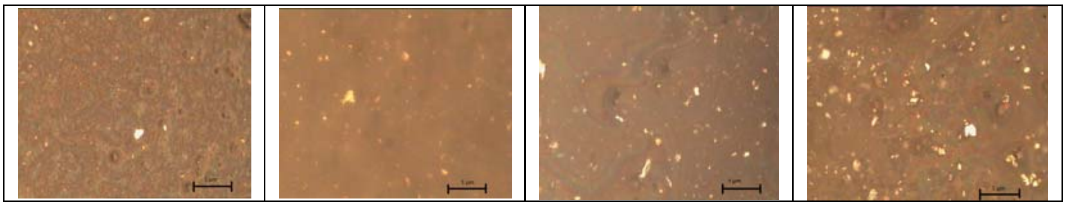


Figure 4: The curves of the other features: (a) roughness, and (b) viscosity.

To compare the IPCA with other features, the variations of the surface roughness of large wear particles and the oil viscosity are given in Figure 4. It can be seen in Figure 4(a) that the order of magnitude of the roughness is too small and the roughness values in abnormal engine operation condition are close to the values in normal condition. Although the roughness in severe faulty condition is larger than that in the slight wear condition, it is still difficult to assess the engine health condition according to the roughness values via the on-line manner. In Figure 4(b), the viscosity curve is similar to the IPCA curve. It can be used to detect the engine fault on-line. However, some singular points may influence the viscosity value significantly, such as the points at 22 and 24 testing hours. This is because the viscosity reflects the wear particle changes to certain degree but other factors may also influence the viscosity variation, such as the oil temperature, etc. In contrast, the IPCA has no such problems and hence is superior to the viscosity in the on-line fault detection. This point of view is also proven by the feature selection results in table 2.

3.3 Discussion

Nine typical features have been extracted by the oil analysis, but not all of them are suitable to be incorporated into the developed diagnosis system. The on-line fault detection performance may vary with the sensitiveness of the features to the changes of the machinery health conditions. It can be seen that the correlation of the IPCA to the engine health conditions in Figure 2 agrees well with the ferrographic images in Figure 3. The initial crack of the gear pump influence little on the lubricant performance of the diesel engine. However, this situation boosts into reverse after 45 testing hours. The IPCA rises up to as large as 450, which warns us that the engine encounters unexpected damages. Hence, the gradually grown crack has broken down the gear pump and a large amount of metal wear particles have been generated. In order to detail this failure mechanism and explain the fault detection mechanism of the IPCA, the filtergram technique was used to analyze the oil samples in an off-line way. A total of 100 filtergram samples were obtained to record the wear progress of the diesel engine from the start of the test to the end. Figure 5(a~d) shows a portion of the filtergrams covering the development experience of the engine health conditions.



(a) 12 testing hours	(b) 24 testing hours	(c) 48 testing hours	(d) 72 testing hours

Figure 5: The filtergrams of the lubrication oil samples

In Figure 5(a), when the engine was in early stage of the test, a small amount of wear debris was generated. The wear of the engine was normal because only a few rubbing particles (<0.1 μm in size) were observed. The size and amount of rubbing particles increased slightly in Figure 5(b) after another 12 testing hours. This means the engine working condition has become terrible. Nevertheless, the wear particle type suggested that the wear of the engine was basically normal. However, the health condition of the engine changed in Figure 5(c~d). Large laminar particles (approximately 3 μm in length) appeared. The severity of the crack failure grew enough to destroy the lubrication boundary of the gear pump, leading to direct contact between the gears. One can be noticed in Figure 5(d) that a large amount of chunky and fatigue particles were generated. These particles are good indicators of lubrication breakdown.

Compared with Figure 5, the IPCA curve in Figure 3 is concordant to the wear progress of the diesel engine. During the period of 40 to 50 testing hours, the IPCA curve changes greatly from normal to abnormal whilst the wear type and size in Figure 5 have similar changes. It is evident that with the development of the gear crack the number of the chunky and fatigue particles increases correspondingly.

From the above analyses, it can be concluded that the metal-to-metal contact caused by the engine fault has generated informative wear particles. By the use of interaction information based feature selection, the most suitable indicator (the IPCA) has been selected to be incorporated into the remote on-line fault diagnosis for marine diesel engines. Satisfactory fault detection performance has been achieved.

4. Conclusions

Any failures in the diesel engines would badly threaten the safety of ships. For this purpose, a new remote on-line diagnosis system has been developed in this work for industrial application of CMFD of marine diesel engines. The constructed remote on-line diagnosis system takes the advantages of tribological information to implement the fault detection procedure. Experiments carried out in the “Changjing 2” dredger show that the newly developed remote on-line fault diagnosis system is competent for fault detection. Hence, the new system is feasible in engineering practice, and efficient for failure detection for marine diesel engines.

Future research is planned to further investigate the intelligent fault diagnosis and decision-making subsystem in the laboratory center. Multi-dimensional sceneries, including the tribological information and vibration signals, will be integrated in the intelligent system. Industry application of this updated remote on-line CMFD system will be explored not only for marine diesel engines but also other machineries in the marine power system.

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References

Brown G., Pocock A., Zhao M., Luján M., 2012. Conditional likelihood maximisation: A unifying framework for information theoretic feature selection, Journal of Machine Learning Research, 13, 27–66.

Jones N. B., Li Y. H., 2000. A review of condition monitoring and fault diagnosis for diesel engines. TriboTest, 6 (3), 267–291.

Kauffman R. E., Ameye J., 2002. Combining on-site and on-line voltammetric analyses to better understand the different degradation mechanisms of industrial lubricants and equipment - Part I: Joint Strike Fighter engine, Lubrication Engineering, 58 (8), 19–26.

Lamaris V. T., Hountalas D. T., 2010. A general purpose diagnostic technique for marine diesel engines – Application on the main propulsion and auxiliary diesel units of a marine vessel, Energy Conversion and Management, 51 (4) 740-753.

Liu J., Yan X., 2010. Study of diagnosis system framework using remote knowledge service, in: Proceedings of the 2010 Prognostics and System Health Management Conference, Macau, China.

Lunt S., 2011. Recent developments in online oil condition monitoring sensors and alignment with ASTM methods and practices, Journal of ASTM International, 8 (7), 86–106.

Markova L.V., Makarenko V.M., Semenyuk M.S.and Zozulya A.P., 2010. On-line monitoring of the viscosity of lubricating oils, Journal of Friction and Wear, 31 (6), 433–442.

Mohammadi L. B., Kullmann F., Holzki M., Sigloch S., Klotzbuecher T., Spiesen J., Tommingas T., Weismann P., Kimber G., 2010. A low cost mid-infrared sensor for on line contamination monitoring of lubricating oils in marine engines, in: Proceedings of SPIE - The International Society for Optical Engineering, Optical Sensing and Detection, Brussels, Belgium.

Ozogan M.S., Khalil A.I., Katsoulakos P.S., 1989. Tribological failure detection and condition monitoring for diesel engines, Wear, 130 (1) , 189–201.

Peng Z., Kessissoglou N., 2003. An integrated approach to fault diagnosis of machinery using wear debris and vibration analysis. Wear, 255(7–12), 1221–1232.

Peng Z., Kessissoglou N., Cox M., 2005. A study of the effect of contaminant particles in lubricants using wear debris and vibration condition monitoring techniques. Wear, 258 (11–12), 1651–1662.

Villar A., Gorritxategi E., Fernandez S., Otaduy D., Arnaiz A., Ciria J., Fernandez L., 2010. Visible/NIR on-line sensor for marine engine oil condition monitoring applying chemometric methods, in: Proceedings of SPIE - The International Society for Optical Engineering, Optical Sensing and Detection, Brussels, Belgium.

Wu T., Mao J., Wang J., Wu J., Xie Y., 2009. A new on-line visual ferrograph, Tribology Transactions, 52 (5), 623–631.

Yan X., Sun J. 2003. Recent progress on the key issues of vehicle operation engineering, China Transportantion Press, China.

Yan X., Zhao C., Lu Z., Zhou X., Xiao H., 2005. A study of information technology used in oil monitoring. Tribol. Int., 38 (10), 879–886.

Yan X., Sun X., Yin Q., Li K., Liu C., 2011. A on-line oil moisture and viscosity detection device for ship condition monitoring, Chinese Pant, No. CN201120276086.2.

Yuan C., Peng Z., Zhou X. and Yan X., 2005. The surface roughness evolutions of wear particles and wear components under lubricated rolling wear condition, Wear, 259 (1–6), 512–518.

Yuan C., Peng Z., Yan X., Zhou X., 2008. Surface roughness evolutions in sliding wear process, Wear, 265 (3–4), 341–348.