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Remaining Useful Life Prediction for Rolling Element Bearing Based on Ensemble Learning

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Information fusion is becoming state-of-the-art methodology for performance assessment of engineering assets. Efficiently and smartly combining multi-source information and relevant models from the interested object, more accurate and reliable diagnostic and prognostic results regarding the object can be achieved, which are especially significant for the condition-based maintenance and prognostics and health management applications. Ensemble learning, as a typical machine learning and decision fusion method, has long been applied in the pattern recognition field and demonstrated promising performance. However, scarce applications of ensemble learning have been found for remaining useful life (RUL) predictions. RUL prediction based on ensemble learning by merging multi-piece information and dynamically updating is proposed in this paper. Specifically, multiple base learners are trained to work as one RUL estimator and weighted averaging with dynamically updated weights upon the latest condition monitoring information is employed to aggregate these RULs to form the final RUL. Rolling element bearing degradation experimental data is used to verify and validate the effectiveness of the proposed method.

1. Introduction

Condition-based maintenance (CBM), which takes the operational conditions of engineering assets into account when scheduling interventions (e.g. repairs, replacements etc.) and thus can greatly reduce the running costs while increase their availabilities and is attracting increasing attention from both academic and industrial domains (Jardine et al., 2006). To practice CBM, prognostics should be carried out to estimate RUL upon all the available information, which is of significance for prognostics and health management (PHM) applications as well (Chen et al., 2012). Methods of failure and reliability predictions (Zio et al., 2012) have become hot topics in various fields.

Generally, RUL prediction methodologies can be filed into three types, i.e. model-based methods, data-driven methods and combinations of the two (Sikorska et al., 2011). Failure-of-physics approaches, such as a Paris crack propagation model, can achieve accuracy RUL predictions but they are also more costly and application specific. On the other hand, data-driven methods, such as artificial neural network (ANN) (Gebraeel et al., 2004), stochastic filtering model (Wang, 2011) and hidden Markov model (Liu et al., 2012), are more generic while their RUL estimation accuracy is compromised. So it seems more promising to fuse these two kinds of methods to perform RUL prognostics. However, there are rare failure-of-physics models that can be used to predict RUL of a component and further work needs to be done in this respect.

To pursue accurate RUL predictions, RUL estimation based on ensemble learning is proposed in this paper and its performance is validated by rolling element bearing degradation experiments.

2. Ensemble learning

Ensemble learning is a typical machine learning paradigm in which more than one learner is constructed on the given information to solve the underlying problem and has been applied in many domains, especially in the pattern recognition problems (Oza et al., 2008). In essence, ensemble learning is also of

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decision fusion category. Though it has not been proved theoretically why ensemble learning can work well, Dietterich (2000) gave three arguing reasons to explain its superior performance.

Implementation of ensemble learning basically includes base learner construction and their results aggregating (Dietterich, 2002). Base learner, such as artificial neural network (ANN), can be constructed by calling the Boosting, Adaboost, stacking, random forests or other algorithms. The second problem that should be accounted is which kind of combining rules should be used to combine the individual results to give the final output. Majority voting, winner takes all and weighted averaging are among the frequently fusing rules in pattern recognition applications, while weighted averaging philosophy has been employed to obtain the ensemble learning regression results.

To achieve better ensemble learning generalization performance, it is realized that accuracies of the base learners and diversities among them are two vital factors. Much work has been dedicated implicitly or explicitly to improve precisions of the base learners and the mutual-differences between the constructed constituents respectively or simultaneously (Wang et al., 2011).

3. Ensemble learning based RUL prediction

3.1 The proposed ensemble learning based RUL prediction approach

The proposed RUL prediction method primarily consists of the off-line learning (Figure 1) and on-line usage (Figure 2) phases and its implementation is detailed as follows.

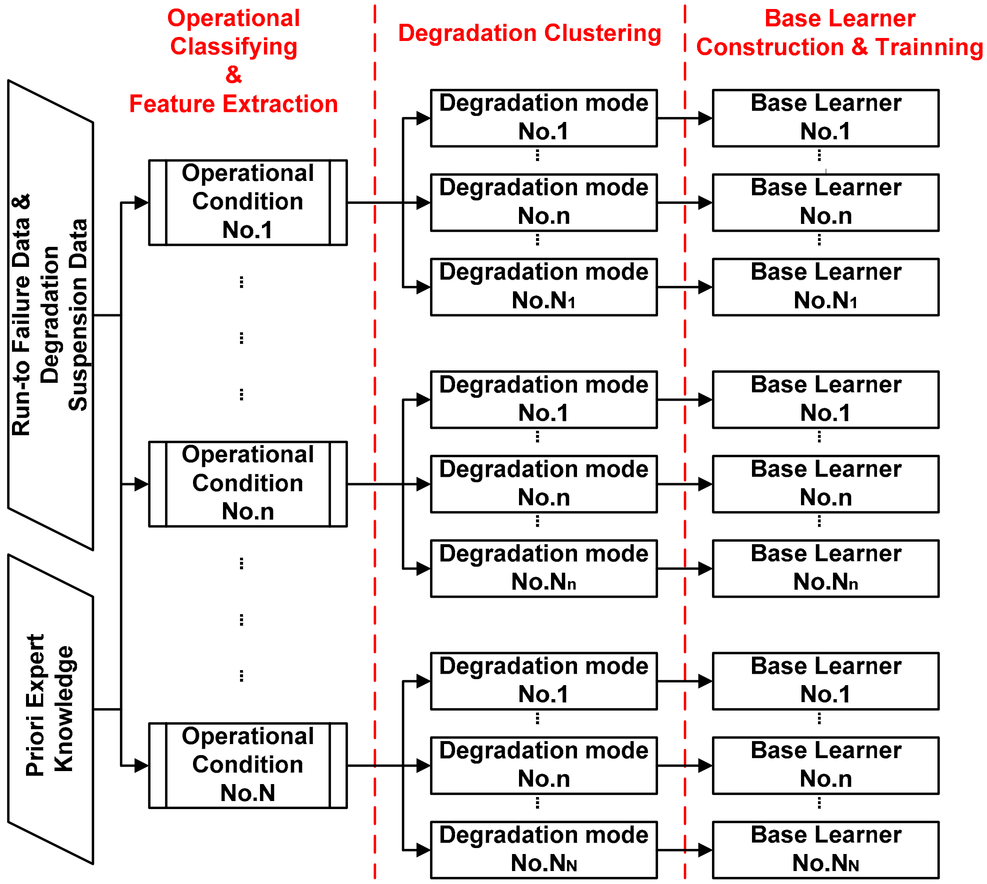

Figure 1: Off-line learning of the ensemble learning based RUL prediction method

Off-line learning process of the proposed RUL prediction method includes three steps. Specifically the historical run-to failure data of the engineering assets is classified into different foreseen running conditions to account for operational and environmental effects. Also, sensitive degradation features should be extracted or selected by pre-processing the multiple sensory signals from the interested objects. Then clustering is employed to cluster similar degradation processes into common degradation modes to reduce the modelling efforts as well as relieving burden of the on-line usage. Finally, base learners are

constructed and trained with the typical deterioration modes. However, in cases where run-to failure data is absent or prohibitively expensive to collect, degradation censored data can work as an alternative.
On-line usage modular of the ensemble learning RUL prediction is designed to perform instant RUL of the engineered artefacts when condition monitoring information is available. Firstly, condition monitoring samples (such as vibration signals) are pre-processed as done in the off-line phase. Secondly, the extracted degradation features are fed into the individual learners to estimate the RUL of the engineering objects and some kind of similarity measures are used to derive the likeness between the instant degradation features and the degradation modes. After that, the weighted average aggregating rule is employed to fuse the individual RUL into the final RUL.

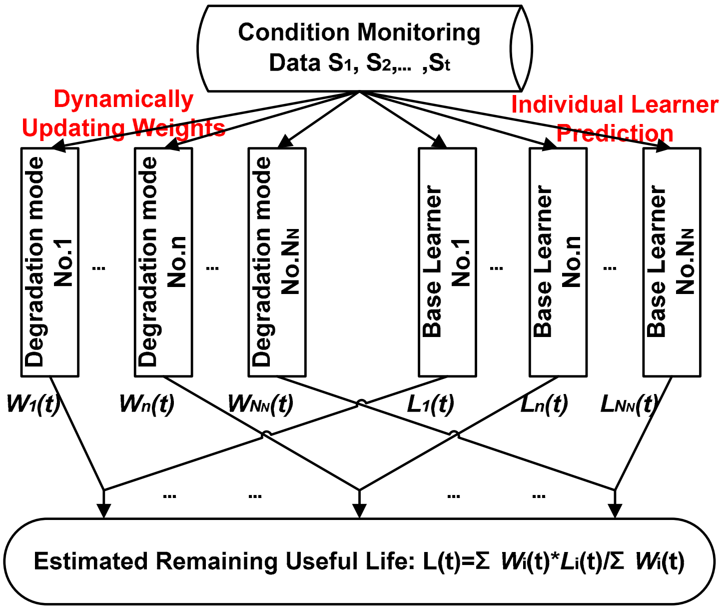

Figure 2: On-line usage of the ensemble learning based RUL prediction method

3.2 Discussions on the proposed RUL prediction method

Diversity of the proposed RUL estimation method is explicitly guaranteed by the multiple degradation modes, while convergence is partially ensured by the clustering. Moreover, dynamically weights updating modular can update the instant weights once new degradation features are present. This is a great improvement over the rare reported ensemble based RUL prediction methods (Hu et al., 2012). Since the true degradation mode of the interested object will be assigned more weight with the consumption of its life and corresponding maintenance can be scheduled before real failure happens.
During the off-line learning phase, historical run-to failure/degradation data is needed to compile a reliable and complete degradation mode pool, which can be costly, time consuming or even prohibitive. Thanks to many established and establishing accelerated life testing experimental and precise simulating platforms, the above issue can be much freed (Nectoux et al., 2012). Computational challenge of on-line dynamical weights updating and individual learner prediction can be managed by properly designing similarity metrics (e.g. probability, distance) and controlling the used historical information (i.e. degradation features preceding the current instant).

4. Rolling element bearing RUL prediction

Bearings are common components in many applications and are also the vulnerable parts, it will benefit a lot to practice CBM based on the estimated RUL (Medjaher et al., 2012). In this section, the ensemble learning-based RUL estimation method was applied to the rolling element bearing RUL prediction.

4.1 Experimental setup

The bearing degradation data is provided by the PRONOSTIA platform, which has been designed and realized at AS2M department of FEMTO-ST Institute (Nectoux et al., 2012). To better simulate "normally" bearing degradation phenomenon, the bearing defects (balls, rings and cage) are not initially initiated on bearings and almost all the types of defects can occur in one bearing during one running. This lays much difficulties on the validation of the dynamically weights updating modular, which is one novel contribution of the proposed RUL prediction approach. However, this will be demonstrated in our future work.

Testing bearings used in the experiment are rolling element bearings with zero contacting angles, and its specifications are tabulated in Table 1. The experiments were controlled that once the amplitude of the vibration signal overpassed 20 g, the testings were stopped and the testing bearings were deemed failures. During the bearing degradation testing, both horizontal and vertical vibration accelerations were sampled with a sampling frequency of 25.6 kHz and each sample had 2.56 k data points, while the sampling interval was 10 s. Six bearings under the 1800 rpm and 4000 N loads operational condition, whose lives ranged from shorter than 4 h to longer than 7 h demonstrating large variations were analyzed here.

Table 1: Testing bearing specifications

Bearing type	Pitcher diameter/mm	Ball diameter/mm	No. of balls
Rolling element bearing	25.6	3.5	13

4.2 Bearing RUL prediction

Initially, 13 time-domain statistical and 16 frequency-domain wavelet packet decomposition nodes energy features were calculated for both horizontal and vertical acceleration signals. Unfortunately, many of them are insensitive to the deteriorations, inconsistencies in the degradation process or uncommon among the tested bearings though the bearings are of the same type and under one usage condition. So variance analysis was performed to identify the much better features since there have been handful reports addressing the degradation feature evaluation issues. Finally, three from the horizontal and one from the vertical direction were selected (Figure 3), which is in consistent with the design of the experimental setup as the load was exerted in the horizontal direction.

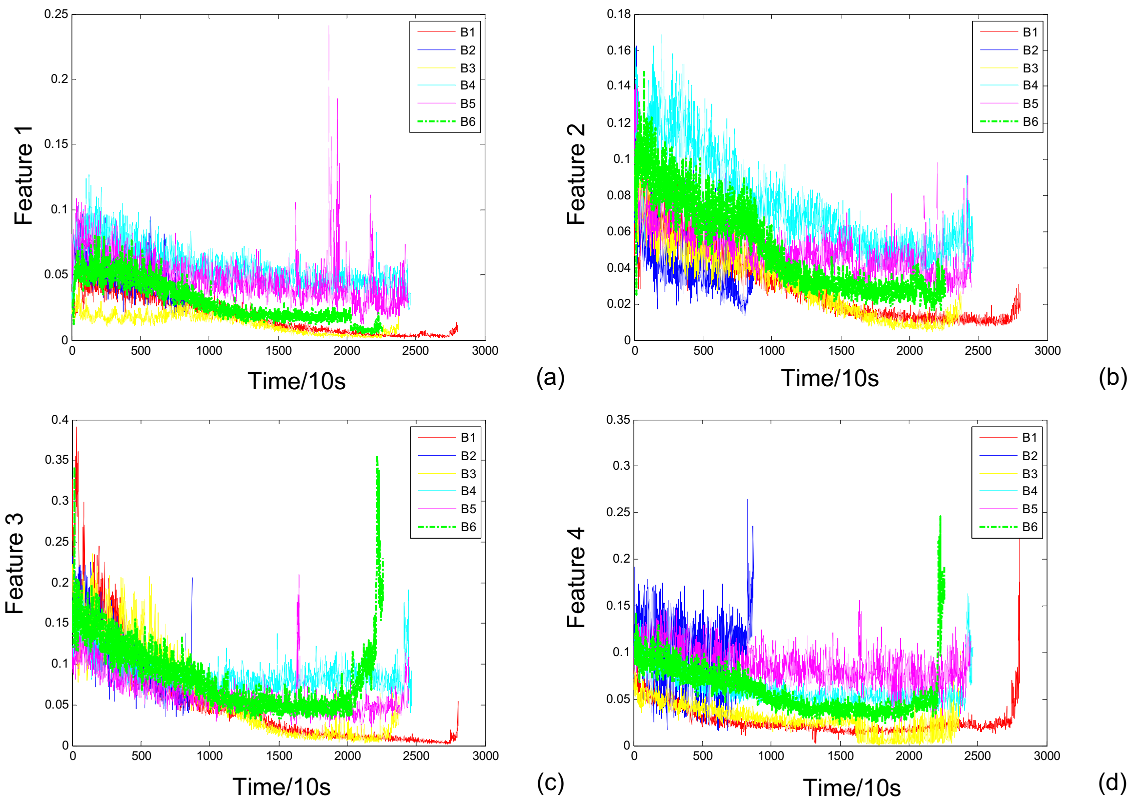

Figure 3: Four degradation features

It can be seen from Figure 3 that Bearing 1, 2 and 3 degraded similarly and Bearing 4 and 5 have the same degradation trend, while the failure progressing of Bearing 6 seems to be between the two degradation modes. Thus two degradation modes clusters (hereafter labelled as D1 and D2) were constructed.

Two 4-16-1 BP-ANNs base learners were constructed and trained with the two degradation modes without any curve fitting or smoothing processing of the four degradation features and Bearing 6 was taken as the testing bearing. Outputs of the BP-ANN were the remaining life percentage, which can be transformed to RUL through simple calculation, and hereafter denoted as RUL.

Bearing RUL prediction results are depicted in Figure 4. It can be concluded that D1-RUL (based on D1) overestimates the RUL and D2-RUL (based on D2) underestimates the RUL of Bearing 6. However, RUL based on ensemble learning (EL-RUL) is better and is a little biased towards shorter RUL, which is conservative and less costly to risk. Prediction relative errors with time elapsing are given in Figure 5(a) and conclusion can be drawn that in most cases the errors of the ensemble learning method (EL-E) are varying within 20 percent. While errors of the D1-E and D2-E are towards larger positive and negative errors respectively. To further statistically analyze the performance of the ensemble learning RUL prediction method, its error histograms are given in Figure 5(b), demonstrating that only 180 RUL predictions, i.e. a little less than 12 percent of all predictions, are not bounded in 20 percent relative errors.

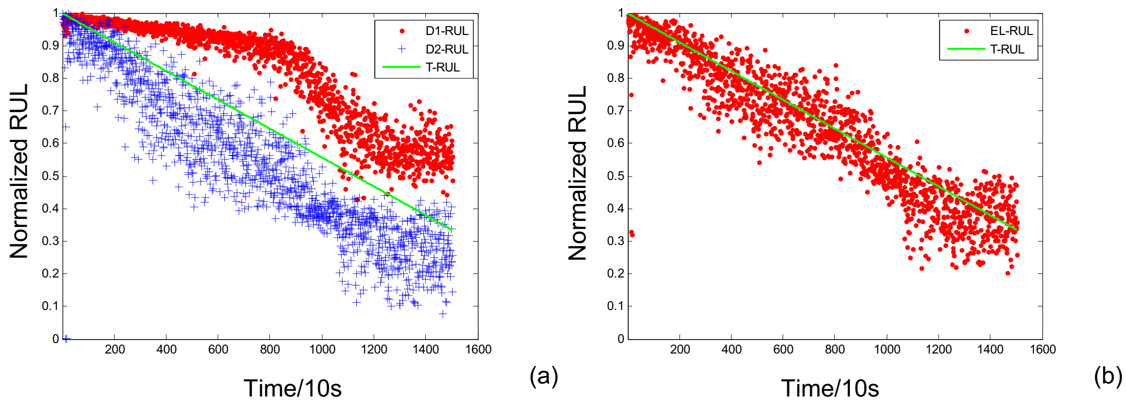

Figure 4: Bearing 6 RUL prediction results

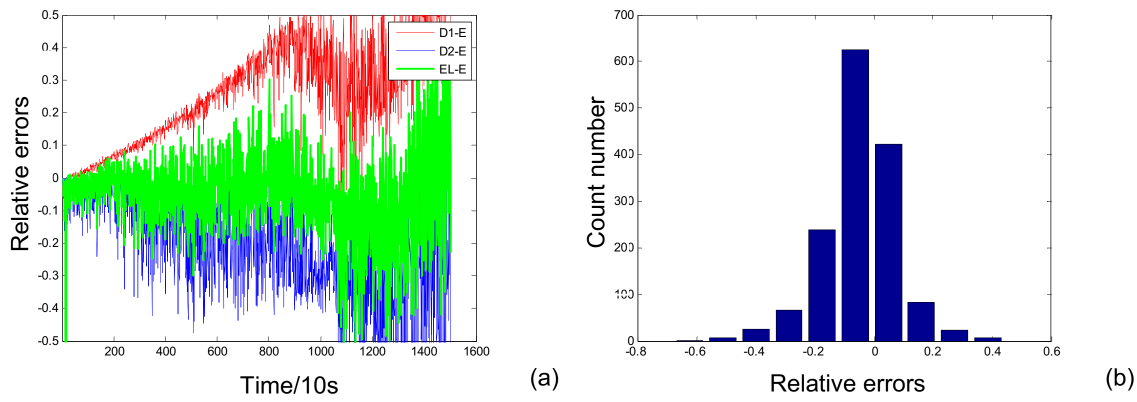

Figure 5: Errors evolving with time and error histogram of the ensemble learning RUL prediction method

However, it is also observed that EL-E errors (Figure 5(a)) deviate more from zero at the end parts of the prediction, which contradicts with intuition that with consumption of the bearing life more accurate RUL predictions are expected (Gebraeel et al., 2009). This may be caused by the large difference of the latter part in the degradation modes (Figure 3) and can be tackled by some smoothing management. Another interesting observation is that more accurate single instant RUL prediction can be obtained by linear fitting since the sampling epochs are equal and thus RUL is linear decreasing with prediction instant. Please note that the weights were not updated dynamically but arbitrarily set as 0.5 for the two degradation modes for simple illustrating purposes on ensemble learning-based RUL prediction and further work should be done to dynamically optimize the weights and better degradation features are also beneficial.

5. Conclusions

RUL prediction based on ensemble learning is proposed in this study and its effectiveness is validated using rolling element bearing degradation data. In essence, the proposed ensemble learning-based RUL prediction method is a combination of feature and decision fusion. With ensemble learning philosophy, operational conditions and degradation modes of the engineering assets are simultaneously included into the modelling process and results of base learners are aggregated to output the final RUL prediction by a dynamically weights updating process which can also indicate the underlying failure/degradation modes.

Although ensemble learning methods have well-established in diagnostics applications, its potentials in RUL prediction have to be explored and much work needs to be followed. Construction of diverse and accurate base learners that output RUL distributions to manage uncertainties and what similarity measures should be used in the dynamically updating are among the future working directions.

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References

Chen Z.S., Yang Y.M., Hu Z., 2012, A technical framework and roadmap of embedded diagnostics and prognostics for complex mechanical systems in prognostics and health management systems, IEEE Transactions on Reliability, 61, 314-322.

Dietterich T.G., 2000, Ensemble methods in machine learning, Lecture Notes in Computer Science, 1857, 1-15.

Dietterich T. G., 2002, Ensemble Learning, The Handbook of Brain Theory and Neural Networks, Second edition, The MIT Press, Cambridge, MA, USA, 405-408.

Gebraeel N., Lawley M., Liu R., Parmeshwaran V., 2004, Residual life predictions from vibration-based degradation signals: a neural network approach, IEEE Transactions on Industrial Electronics, 51, 684-700.

Gebraeel N., Elwany A., Pan J., 2009, Residual life predictions in the absence of prior degradation knowledge, IEEE Transactions on Reliability, 58, 106-117.

Hu C., Youn B.D., Wang P.F., Yoon J.T., 2012, Ensemble of data-driven prognostic algorithms for robust prediction of remaining useful life, Reliability Engineering & System Safety, 103, 120-135.

Jardine A.K.S., Lin D.M., Banjevic D., 2006, A review on machinery diagnostics and prognostics implementing condition-based maintenance, Mechanical Systems and Signal Processing, 20, 1483-1510.

Liu Q.M., Dong M., Peng Y., 2012, A novel method for online health prognosis of equipment based on hidden semi-Markov model using sequential Monte Carlo methods, Mechanical System and Signal Processing, 32, 331-348.

Medjaher K., Tobon-Mejia D.A., Zerhouni N., 2012, Remaining useful life estimation of critical components with application to bearings, IEEE Transactions on Reliability, 61, 292-302.

Nectoux P., Gouriveau R., Medjaher K., Ramasso E., Morello B., Zerhouni N., Varnier C., 2012, PRONOSTIA: an experimental platform for bearings accelerated life test, IEEE International Conference on Prognostics and Health Management, Denver, CO, USA.

Oza N.C., Tumer K., 2008, Classifier ensembles: select real-world applications, Information Fusion, 9, 4-20.

Sikorska J.Z., Hodkiewicz M., Ma L., 2011, Prognostic modelling options for remaining useful life estimation by industry, Mechanical Systems and Signal Processing, 25, 1803-1836.

Wang W.B., 2011, Overview of a semi-stochastic filtering approach for residual life estimation with applications in condition based maintenance, Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability, 225, 185-197.

Wang S., Yao X., 2011, Relationships between diversity of classification ensembles and single-class performance measures, IEEE Transactions on Knowledge and Data Engineering, 25, 206-219.

Zio E., Broggi M., Golea L., Pedroni N., 2012, Failure and reliability predictions by infinite impulse response locally recurrent neural networks, Chemical Engineering Transactions, 26, 117-122, DOI: 10.3303/CET1226020.