Enhanced System Health Assessment using Adaptive Self-Learning Techniques

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ABSTRACT

System health assessment, as one of the most critical tasks in Prognostics and Health Management (PHM), is able to determine the current health condition and detect the incipient fault. Conventionally, the assessment is executed by evaluating the difference between the current behavior and a pre-defined baseline model through the training data. However, only relying on the static baseline model might not obtain an accurate health assessment result in practice, since the dynamic data context will lead a tremendous impact on the assessment decision. This research proposes to design and develop a systematic approach to assess the system health condition with adaptive self-learning techniques. The proposed method learns from the monitoring process continuously so that it is able to not only prevent the uncertainties in the ambient environment but also aggregate valuable knowledge such as new working regimes or degradation patterns. A growing health model is constructed to accumulate newly encountered working regimes and degradation patterns. Finally, the whole methodology was validated by a toy data set from a rotor shaft test bed, which demonstrated the feasibility of the self-learning mechanism.

1. PROBLEM STATEMENT

Maintenance and health management of the machine or the process have played a critical role in industry. Both the academia and the industry have contributed to developing advanced strategies and techniques maintaining the machine properly while preventing unexpected down time. In last decade, with the growing of the sensing technology and the networked monitoring system, the conventional "fail and fix" practices have been transforming to "predict and prevent" strategies (Lee, 2003).

An effective health assessment acts as the root of predictive analytical tasks since the current health condition must be determined before employing the diagnostics or prognostics. An accurate health assessment can help understand if the machine or the system works under healthy condition or already under degradation states. Timely incipient fault detection (Chandola, Banerjee & Kumar, 2009) is also able to trigger further analysis such as diagnosing the root cause of the precursor and predicting the time to failure.

There are three key factors in the health assessment: the reference or the baseline, the difference quantification, and the threshold. A well-defined reference and an accurate difference quantification reveal the distance between the current status and the healthy condition clearly while an optimal threshold indicates if the machine transfers to a degradation stage and then provides actionable information. However, the health assessment performs excellent only if the baseline is comprehensive enough and the monitoring process is stable. In practice, the assessment result is vulnerable to the unknown factors in the context of the data. Firstly, the uncertainty of the system itself (Youssef, Delpha & Diallo, 2016) would bring overmuch false alarms. Secondly, since it is difficult to construct a comprehensive baseline in the beginning, the detected anomaly might not represent the precursor but a new working regime or an ambient impact (Filev et al., 2010). Therefore, the aforementioned issues necessitate a health assessment technology which can adapt to the system variance, intelligently detect the working regime shifts and differentiate them from the true degradation, and autonomously learn from the assessment results.

This research proposes a systematic health assessment methodology with adaptive self-learning capabilities. In this online analysis approach, the constructed health model will not only adapt to the uncertainties in the testing data, which prevents a large amount of false alarms, but also learn new patterns from the testing data and retrain itself autonomously.

2. EXPECTED CONTRIBUTIONS

A systematic framework is proposed to realize the adaptive self-learning health assessment. The proposed framework evolutionarily transferred conventional health assessment strategy with a static health model to an advanced monitoring activity with a self-learning model. It enables the adaptability of the assessment.

The proposed health model grows conditionally and autonomously. The self-leaning health model does not update every single time but grows based on a specific event. Also, the growth of the health model and the event trigger are executed autonomously without too much human intervention.

The health model can retrain itself in two different directions so that it is able to include both new working regimes and new machine degradation stages. Learning those useful patterns by one model has been realized.

The proposed approach is going to generate a comprehensive health library and then contributes to the construction of the cyber world for the machinery system. The constructed health library bridges the relationship between the physical machine and its invisible cyber world, in which a comprehensive profile about the machine including the operation, the failure, the degradation pattern, etc. is built.

3. RESEARCH PLAN

A flowchart of the proposed methodology is shown in Figure 1. At first, two self-learning models, which are regime model and health model, are initialized by the training features respectively. The regime model is built through the regime related features while the health model is constructed by both the regime features and the health related features. Referring the baseline models, the relevant thresholds are calculated. Thereafter, in monitoring, instead of evaluating each testing observation one by one, a buffer is designed so that a batch of data will be tested every time. The size of the buffer is predefined. In this buffer, the regime features will go through a regime identification process firstly. If a new regime is detected, which indicates that an anomaly has been detected by the regime model, both the regime model and the health model will be updated. The new regime is clustered and added to the regime model while the health model is grown to include the new baseline patterns under such regime. An assumption is described that the model always learns the healthy behavior firstly for the new regime identified.

Once the regime has been identified, the health value is calculated. It is then input to an adaptive health value filter which tunes the threshold adaptively and automatically so that the model will adapt to the uncertainties in the testing data. In the next step, a decision is made: 1 the system performs like the baseline; 2 there are suspicious samples, which might represent the new degradation level. For the former decision, a new batch of data will be included in the buffer and a new assessment will be employed. For the later decision, after evaluation, the health model will be updated again if a new degradation pattern is discovered. The updated health model will be applied on the newly measured features directly once it is completely retrained. Eventually, starting from the scratch, the health model will become extremely comprehensive so that the working regime alone with the possible degradation level are able to be identified and learned.

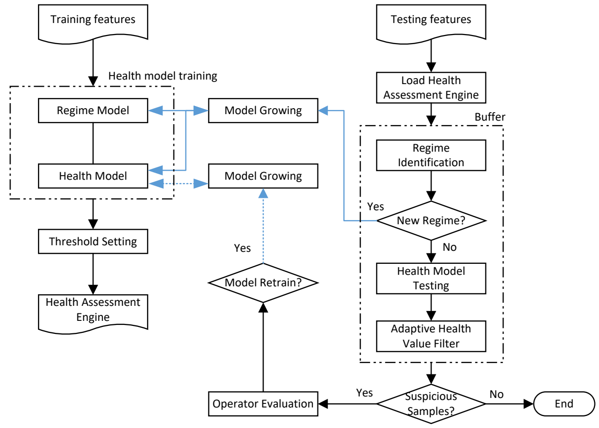


Figure 1. Flowchart of the methodology

The research tasks in this study are summarized as follows:

1. Literature review on adaptive learning and self-learning
2. Develop the self-learning technique
3. Develop the health value filtering approach
4. Demonstrate the proposed approach by one test bed and two real world industrial cases
5. Complete the dissertation and make the defense

3.1 Work Performed

After a comprehensive literature review, an algorithm, named Growing Hierarchical Self-Organizing Map, was selected and modified to realize the self-learning mechanism. The GHSOM has a hierarchical structure with multiple layers (Rauber, Merkl & Dittenbach, 2002). Each layer contains several growing SOMs. The map in each layer grows independently to represent the input data. A new sub layer will be created if the parent map still cannot capture the details in the data. A graphical structure of a GHSOM is shown in Figure 2. During the online monitoring, the trained map will expand to have more nodes in one map or have more layers if a new working regime or a new degradation level is detected.

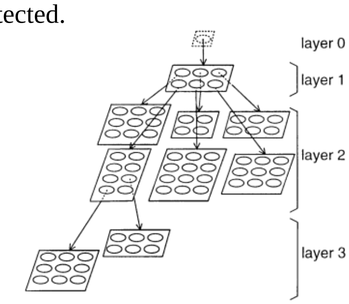


Figure 2. Structure of GHSOM

The proposed self-learning method was demonstrated to assess the health condition of a shaft from a rotor test bed, which is illustrated in Figure 3. One failure mode, which was shaft unbalance, was induced and the vibration data under both the healthy condition and the degradation condition were measured. Besides, the test bed operated under two different rotating speeds, which indicated various working regimes.

Figure 3. Rotor shaft test bed

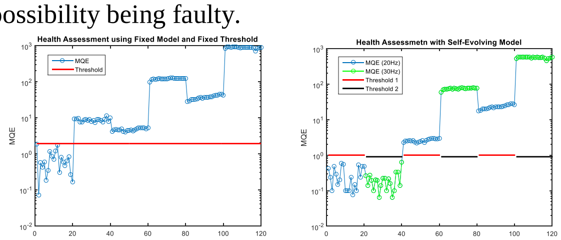
In order to evaluate the self-learning capability of the method, the data training and testing process were designed as follows:

Training: the data utilized for training were vibration data under healthy condition. The working regime was 20Hz. Testing: There were 6 tests implemented in sequence, which were shown in Table 1. The Tests simulated a machine degradation process from healthy to severe unbalance fault.

Table 1. Experiment design

Test #	Input data in sequence
1	Healthy (20Hz), Healthy (30Hz), Unbalance Level 1 (20Hz), Unbalance Level 1 (30Hz), Unbalance Level 2 (20Hz), Unbalance Level 2 (30Hz)

The health assessment results are shown in Figure 4. The proposed method was benchmarked with a conventional health assessment method, which relied on a static health model with a fixed threshold. The SOM was utilized to train such health model. Figure 4 (a) shows the assessment results with the static model while Figure 4 (b) indicates the assessment results with the self-learning model. The red line or the black line represents the threshold, above which there is high possibility being faulty.



(a) (b)

Figure 4. Health assessment result

As illustrated in Figure 4 (a), the healthy behavior under 30Hz working regime is incorrectly recognized as the degradation behavior by the static model. Consequently, numerous false alarms will come out. In the contrast, as shown in Figure 4 (b), the self-learning model autonomously identifies the new working regime and learns this pattern, so that these testing data can be described as healthy. Further, the data with another working regime are labeled by the health model automatically, which represent a different color. Operators can receive more accurate machine information from the analysis.

3.2 Remaining Work

In the experiment, the monitoring process was stable and there was only one failure mode in the system. The uncertainty issue in the testing data was not considered. The adaptive filtering method needs to be studied in the future so that it can deal with the uncertain variations in the testing data. And both the self-learning and the adaptive filtering will be combined to employ the final health assessment. In addition, New experiments are required in the future to induce more factors such as more failure modes. One or two real world industrial cases will be also investigated to validate the methodology in practice.

4. CONCLUSION

In conclusions, a systematic online health assessment methodology has been proposed to autonomously learn the new emerging patterns in the testing process. The constructed health model will retrain and update itself if a new regime or a new degradation level is identified. And the uncertainties in the testing data will not influence such decisions. The feasibility of the self-learning technique was verified by the experimental data set. The health assessment results demonstrated that being compared with the traditional approaches, the proposed method could provide much more detailed information thus prevent many false alarms.

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