Combination of Fusion and Preprocessing Techniques to Enhance Air Vehicle HUMS

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Abstract

A Condition-Based Maintenance (CBM) program calls for transitioning from making time based part replacement decisions to performing maintenance upon evidence of need. For the U.S. Army's CBM+ plan this entails eliminating the use "time before overhaul" (TBO) definitions currently driving vehicle component maintenance schedules. Although Health and Usage Monitoring Systems (HUMS) have the potential to support this goal, their ability to diagnose component faults early is limited, and implementation of prognostics is rare. These limitations are driven partly by the sensitivity of diagnostic processes to signal noise and changes in operating conditions. A representative example is a bearing in the oil cooling subsystem of H-60 helicopters. This paper discusses certain signal processing techniques to enhance early detection capabilities, reduce false alarms in diagnosis, and provide a basis for prognostics. Actual H-60 bearing vibration data and surrogate-bearing test rig data are utilized to illustrate the advantages of the techniques presented.

Keywords: air vehicle diagnostics, feature fusion, diagnostic enhancement, prognostics, air vehicle HUMS, helicopter drive train monitoring.

Introduction

In recent years, the U.S. Army has witnessed various helicopter component failures that are currently driving the need for improved health monitoring and fault prediction that will be implemented under the broader initiative for Condition Based Maintenance (CBM) of the U.S. Department of Defense, known as CBM+. The fault diagnosis and failure prognosis problem for critical helicopter parts/components has been addressed over the years via a variety of model-based and data-driven approaches. Research in this area has focused primarily on the analysis of vibration data and the derivation of condition indicators, component seeded fault testing and detection/identification of incipient failures. Existing hardware/software health monitoring systems, such as VMEP/MSPU [1] and IMD-HUMS/IVHMS [2], collect vibration and other pertinent flight regime data, carry out data pre-processing, and attempt to detect a fault condition using condition or health indicators derived via data processing algorithms. However, with prognostics being an underdeveloped element of CBM and Prognostic and Health Management (PHM) systems, attempts at predicting the remaining useful life of failing components, as well as developing supporting technologies that enhance detection capabilities have been limited in number and scope.

To specifically address improvement of fault detection and failure prediction methods, the Army Research Laboratory, Impact Technologies, LLC, and the Georgia Institute of Technology are currently working collaboratively to develop, test and evaluate modular software components that provide enhancements to diagnostic systems already in service, as well as add failure prognosis capabilities for critical Army aircraft components. This work is being carried out as part of the three-year “Air Vehicle Diagnostic and Prognostic Improvement Program” (AVDPIP), and its ultimate goal is to allow the modular software components to complement existing Army Digital Source Collector (DSC) systems so as to provide the Army with tools and an architecture that support the CBM+ goals of improving readiness, safety, and maintainability of assets. Use of these technologies should warn operators and field commanders of impending failure conditions and assist maintainers in optimizing aircraft repair, maintenance and overhaul practices.

Since the design of an effective prognostic system is one of its primary objectives, the AVDPIP program is developing what is here referred to as “health based” prognostic algorithms, which we identify as those preceded by diagnostic operations that are used to determine the health state of a system and establishing the amount of damage present in a degrading component. This is in contrast to performing what we refer to as “usage based” prognostics, where the state of the component is not regarded before predicting life remaining; instead, usage based prognostic systems keep track of all use of the system and determine life remaining at a given instant by subtracting accounted-for use from a pre-specified life limit.

In general, a CBM program calls for transitioning from time based part replacement decisions to performing maintenance upon evidence of need. This requirement is more wholly fulfilled by the joint operation of diagnostic and health based prognostic systems. For the U.S. Army’s CBM+ plan there is interest in implementing fault detection and PHM algorithms that eliminate burdensome inspections and use of “time before overhaul” (TBO) definitions, which currently drive maintenance and retirement schedules of certain mechanical components in vehicles. Clearly, the first step in reducing dependency on flight hour definitions is to implement effective fault detection technologies. It is widely documented how detecting serious faults in a variety of rotorcraft components before they fail completely is possible, most notably utilizing vibration based diagnostics in aircraft Health and Usage Monitoring Systems (HUMS) such as the Army’s DSC systems currently in use. Arguably, however, the ability of some of these techniques to diagnose component faults in their early stages in vehicle drive systems is limited, and, as will be discussed below, this limitation presents an opportunity to implement advanced detection techniques. Another means to support the elimination of flight hour-based maintenance decisions is the implementation of health based prognostics. However, the task of prognosis is often underrepresented in the field, partly because effective health based prognostic systems require more robust and reliable diagnostics of incipient faults than is sometimes available.

The ability of diagnostic systems to detect early-stage faults is limited to some extent by the sensitivity of data processing, fault detection, root cause classification to signal noise, specific component fault modes, and variations in environmental and operating conditions (such as loads, speeds, flight regimes, etc.) [3]. Thus, there exists the potential to improve vehicle health monitoring algorithms such that they become more insensitive to signal noise and to changes in environmental/operating conditions. Since early detection is a key requirement for the implementation of effective prognostic algorithms, techniques that can mitigate the effects of noise and environmental/operating conditions, as well as perform fault identification, pose themselves as a prerequisite for making prognostic technologies more ubiquitous. This paper reviews some considerations and data fusion techniques to support the aforementioned goals.

Application Example: H-60 Helicopter Bearings

A representative example of the challenges described above is given by a bearing inside the oil cooling subsystem of the H-60 series of helicopters currently in service for the U.S. Army. The Army and Sikorsky Aircraft Corporation have identified the Oil Cooler Fan Assembly as a candidate for CBM maintenance, so engineers and program managers are working together to incrementally increase the TBO life limit until it is no longer necessary. For example, reference [4] identifies methods for gradually increasing the TBO and then moving the oil cooler to on-condition maintenance by considering the different fault modes of the components of oil cooler assemblies, such as the bearings, shafts, splines, housings, and fan blades. Of all these components, the present paper is focusing on the fan support bearings. The transition from flight hour-based (using TBO definitions) to condition-based maintenance for this bearing is of interest due to the criticality of the component and the relatively high incidence of replacements and faults [5]; additionally, the bearings are in limited supply and offer potential availability of data collected from a variety of helicopters in service [4].

Based upon a CBM credit requirements document published by the FAA (AC29-2C MG 15), ref. [4] defines requirements for the Army to approve the elimination of use of the UH-60 Oil Cooler Fan Assembly TBO, thereby moving to on-condition health monitoring. An important consideration proposed therein is the use of three different categories (light, moderate or severe) for classifying damage corresponding to different fault modes of components based on experience and UH-60 Maintenance Manuals. Table 1, which has been abridged from [4], presents the corresponding classification for just the bearings and the shaft as an example.

Table 1. Damage and Fault Classification Guide (Abridged from [4]).

Component	**Fault**	**Damage Classification**		
		Light	***Moderate***	***Severe***
Bearing	Corrosion	Up to 30% surface area	30% to 60% surface area	60% or greater surface area
	Spall	Up to 30% surface area	30% to 60% surface area	60% or greater surface area
	Fracture	Less than 20%	20% to 50%	Greater than 50%
	Looseness	90% to 100% of the allowable	100% to 150 % of the allowable	150% or greater of the allowable
	Wear	90% to 100% of the allowable	100% to 150 % of the allowable	150% or greater of the allowable
Shaft	Corrosion	Up to 10% surface area	10% to 20% surface area	20% or greater surface area
	Fracture	Less than visible	Any visible crack up to 10% of circumference or 1 in length	10% of circumference or 1 in length
	Looseness	90% to 100% of the allowable	100% to 150 % of the allowable	150% or greater of the allowable

A key enabling factor of the safe transition to effective CBM can clearly result from the implementation of a bearing life prognostic system. However, as mentioned earlier, to be most effective, the operation of such a prognostic system must be preceded by, and integrated with, enhanced diagnostic algorithms capable of detecting a fault in its early stages of development.

These diagnostic operations should perform robustly even in the presence of the multiple kinds of disturbances affecting data acquired by DSC sensors.

Oil Cooler Assembly of the H-60

The oil cooler is a core component of the H-60 tail rotor drive train assembly whose primary function is to cool the helicopter transmission lubricant while transmitting power to the tail rotor drive shaft through the oil cooler shaft. It sits in the downdraft of the main rotor wash, and uses a fan to force air through a radiator for efficient cooling. The tail rotor drive train consists of a drive shaft that transfers torque from the main transmission to the oil cooler drive shaft and then to a series of drive shaft sections and the intermediate gear box before propelling the tail rotor gear box. This arrangement is shown in Fig. 1.

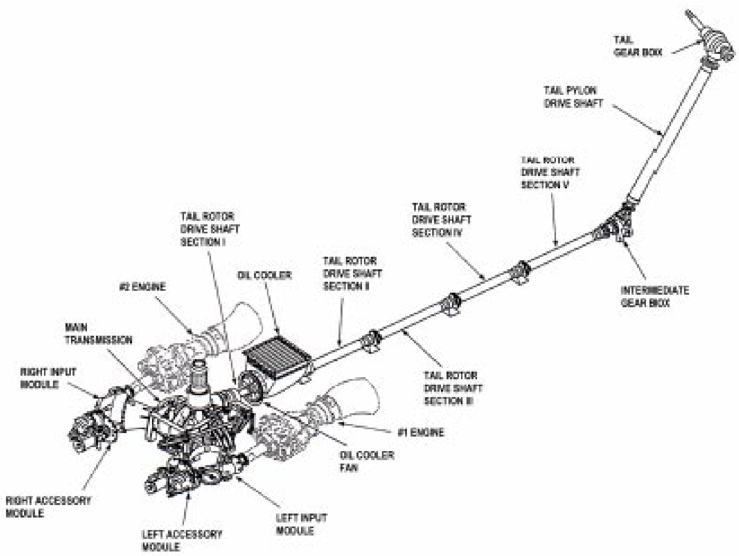

Fig. 1: H-60 drive train assembly (From "Technical Manual, Aviation Unit and Intermediate Maintenance for Army Models UH60A, UH60L, and EH60A Helicopters", U.S. Army TM 1-1520-237-23-4, May 29, 1998)

The components of the oil cooler, illustrated in Fig. 2, are centered on a splined shaft supported at the front by two shielded cartridge bearings, and in the rear by a viscous damper bearing. The oil cooler fan assembly consists of a multi-bladed rotor housed inside a concentric stator. The shields of the bearings contain the grease supply inside the bearings and protect the latter against contaminants such as dust and debris.

Fig. 2: H-60 oil cooler components.

Fault analysis of the shielded cartridge bearings supporting the fan of the oil cooler carries high relevance since failure of these components may cause the tail rotor drive shaft to shear, resulting in power loss to the tail rotor. The fan support bearings are deep-groove, grease-packed ball bearings. They are standard mobility application bearings with an inner bore diameter of approximately 2 inches, 10 balls and specified to ABEC-1. A pair of identical bearings (fore/aft) is present on the fan shaft of the oil cooler assembly. Bearings with heavily contaminated grease and exhibiting corrosion on the raceways, balls and cage surfaces have been found in the field in multiple instances (see, for example, [5]), particularly on the front cartridge bearing. Grease breakdown and wash-out are also fault modes of concern. Fig. 3 illustrates some of these fault modes.

Fig. 3: Oil cooler bearing degradation: corroded inner raceway (left) and outer raceway (middle), and damaged bearing ball (right).

A 2000-flight hour life limit was originally imposed on the bearing, based upon an assumed yearly flying-hour program and a 5-year shelf life of the grease. It is believed that such a number is overly conservative, because of increased OPTEMPO and since operating temperatures drive out water vapor, and failure is unlikely under the observed corrosion conditions and the support of the back bearing. Still, with no substantial backing of this claim, the Army is concerned with the prospect of having to service a multiplicity of platforms as the 2000-hour life limit approaches. Due to the prospects for life extension, there is great potential benefit in the development of a reliable monitoring and condition assessment system for the oil cooler bearings.

Bearing Fault Effects and Monitoring

The phenomenon of rolling contact fatigue has been long known to be a leading contributor to the failure of rolling element bearings. This failure mode is instigated by the cycling loading profile generated by the Hertzian contact forces rotating circumferentially about the ball/raceway during bearing motion. The resulting sub-surface stress cycles eventually lead to the flaking away of raceway material referred to as "spalling." Once a spall is present on the bearing raceway, the continued stress cycles will result in the loss of additional material and growth of the spall. Once a raceway spall reaches a size deemed harmful to the safe, reliable operation of the system, the bearing is said to be failed.

Previous bearing studies and practical usage experience have indicated that the presence of raceway surface corrosion can greatly accelerate the spalling process. The accepted physical explanation for this effect is that the formation of corrosive pitting on the raceway provides an ideal location for spall initiation. It is also very likely that the brittling effects of corrosive degradation accelerate the rate of spall growth. The combined corrosive/fatigue degradation of roller bearings is a failure mode of great interest in bearing systems that are exposed to environmental conditions such as moisture and humidity that instigate the corrosive process.

Helicopter drive train and accessory bearings are particularly susceptible to this failure mode, and the H-60 oil cooler fan bearings are no exception. These components can operate in highly corrosive environments, and events like salt water induction or depot washdowns can lead to high levels of corrosive degradation. There is the potential for this corrosion to contribute to the early spalling and eventual failure of the bearing. As mentioned earlier, this component has been deemed a good candidate for the study and development of bearing diagnostic enhancement technologies and health based prognostics, and the failure mode described above is the focus of this paper.

The fault modes of the oil cooler bearing described have been shown to be detectable through vibration analysis [6]. The predominant sensing scheme consists of accelerometers mounted on the oil cooler housing. Vibration data for bearing fault detection consists of time series of accelerometer readings. When a spall has initiated, bearing specific frequencies associated with the location of the defect are excited. However, for the case of corrosion, it is expected that multiple frequencies, or even wideband excitation, will be present. The amplitude and time duration of the defect frequency are expected to be indications of defect severity. Various features or condition indicators, both in the time and frequency domain, are expected to serve as a means for detecting these faults, in agreement with standard vibration based bearing health monitoring.

Example Bearing Vibration Data

The present paper is focusing on two sets of bearing vibration data to illustrate typical diagnostic procedures as well as some of the enhancements currently being developed under the AVDPIP program: (1) samples of actual aircraft data provided by the U.S. Army, and (2) bearing vibration data generated by Impact Technologies through its in-house high-speed bearing test rig.

The first data set corresponds to the vibration signals of an oil cooler fan support bearing from an H-60 helicopter in recent service. The bearing vibration exhibited abnormal, increasing levels on multiple condition indicators calculated by the VMEP DSC system. The bearing was eventually replaced (in June of 2007), as confirmed by the logistics records of the U.S. Army. The second data set of focus in this paper corresponds to vibration data collected from a bearing test rig. This data corresponds to an industrial bearing exhibiting a progressing spall. This bearing is being considered as a surrogate for illustrative purposes, since it provides sufficient data to illustrate some of the techniques discussed in the present document.

Diagnostic Enhancement Algorithms

As described earlier, to arrive at an architecture that offers reliable fault detection and accurate assessments of the remaining useful life of the components, enhanced diagnostic and prognostic algorithms must be implemented. The AVDPIP program is thus focusing on developing a set of software components that provide diagnostic enhancements and failure prognosis algorithms [7]. The effectiveness of these components will be tested initially on diagnosing and prognosticating damage on oil cooler bearings. Although these developments are currently ongoing, this paper reports on progress made and some preliminary results on certain diagnostic enhancements being developed. The two sets of vibration data described earlier (DSC bearing vibration and surrogate bearing test data) are thus used to illustrate the application and effectiveness of some of the diagnostic enhancement techniques under development.

The main goal of the AVDPIP program is not to develop an entirely new diagnostic system, but rather to develop techniques that can be utilized by the Army to improve the performance of their diagnostic systems already in use. The techniques listed below were thus implemented and have been used to obtain the results reported in later sections

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- ImpactEnergy™ Shock Pulse Amplification software, utilizing a multi-step signal processing routine prior to feature extraction that increases the visibility of shock-pulse events indicative of specific bearing faults, thus uncovering frequency spectrum peaks that are otherwise hidden in the broadband spectrum, and allowing for detection of faults in their incipient state.
- Use of an Active Band Selection (ABS) algorithm, which maximizes fault detection by using techniques to identify the best regions of the broadband spectrum to perform fault frequency demodulation (potential system resonances).
- Feature fusion techniques to combine multiple feature values into a single indicator that maximizes fault class separation, increases fault detection confidence and simplifies threshold metrics.
- Sensor fusion techniques to combine the vibration signatures of multiple sensors to decrease the effects of random noise and increase the visible of subtle signs of fault.
- A methodology to detect as early as possible with specified degree of confidence and prescribed false alarm rate an anomaly or novelty (incipient failure) [8].

A hybrid and systematic approach to sensing, data processing, fault feature extraction, fault diagnosis, and failure prognosis has been utilized with the two vibration data sets of focus in this paper. The system architecture contains generic components/algorithms building on model based and data driven methodologies that will eventually be transferable to other critical helicopter systems/components, as illustrated in Fig. 4.

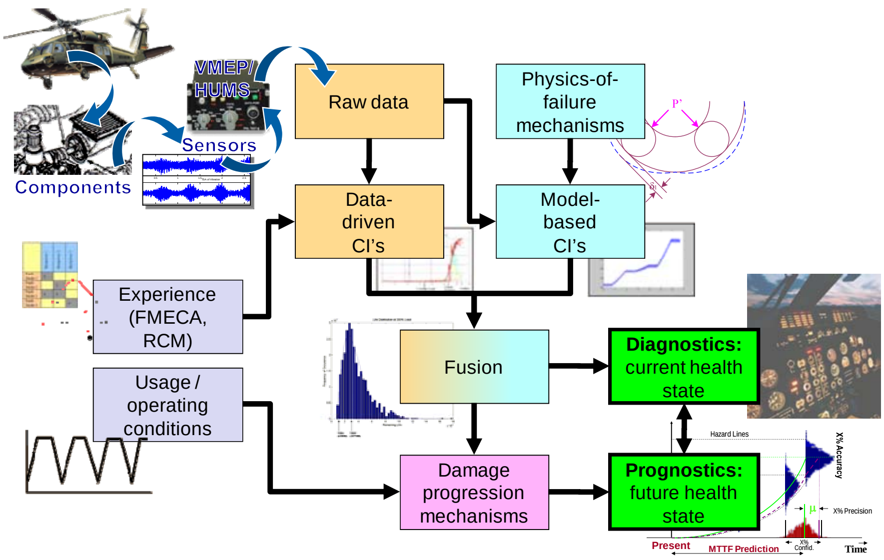

Fig. 4: Overview of the technical approach of the AVDPIP program.

While the oil cooler bearing example was used to demonstrate the developments and achievements of the base period of performance of AVDPIP, the algorithms and methodologies for performing enhanced feature extraction and fusion, developing and combining data-driven and model-based approaches for system health assessments, and managing uncertainty, will be transferable to a wide variety of components and platforms.

Example of Diagnostic Enhancements using Bearing Vibration Data

The techniques discussed above were applied to the two bearing vibration datasets of focus. The first dataset was obtained from an H-60 rotorcraft that experienced an oil cooler related event occurring around the 2006 to 2007 timeframe. Unfortunately the available maintenance information did not provide specific indication of the motivation for this action. Since this rotorcraft data example lacks ground truth information as to the nature of the fault and the aircraft data only includes one sensor, results from a second bearing dataset are presented to further demonstrate the techniques reviewed in this paper. Such second dataset was generated on an experimental test stand using a surrogate bearing with data from three accelerometers.

H-60 Dataset

The ImpactEnergy™ software package was applied to the H-60 dataset. A full feature set was calculated that included statistical time domain metrics and frequency domain energy based quantities. For the purpose of comparison, a set of conventional features were derived using the raw vibration data prior to the data processing operations.

Fig. 5 provides feature trend plots for the RMS value of both the conventional broadband and ImpactEnergy conditioned vibration data. Note that all feature values have been normalized on a 0-1 scale. Both of the feature plots clearly demonstrate a generally increasing trend of RMS values with a large jump in magnitude experienced in mid 2006. The feature values obtained after the ImpactEnergy processing experience lower levels of variance than those from the conventional domain. This effect is most clearly observed in the earlier, presumed healthier data.

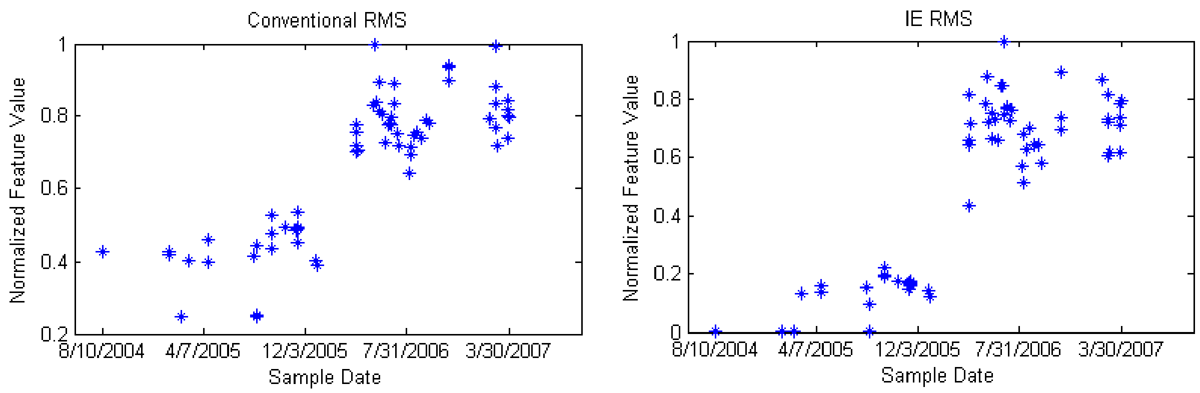

Fig. 5: RMS Trends for H-60 Vibration Data.

While the exact location and nature of the event that instigated the vibration signature change is unknown, the inner race fault frequency (Fig. 6) provides a clearer trend than any of the other component frequencies (outer race, ball pass, cage). Due to the relatively low frequency resolution caused by the short duration of the time sample, it is unclear if this fault frequency response is due to a fault condition located on the inner race or merely a general increase in the energy recorded by the accelerometer. The resulting feature trends again demonstrate that the ImpactEnergy process reduces the feature variance observed in the early time samples.

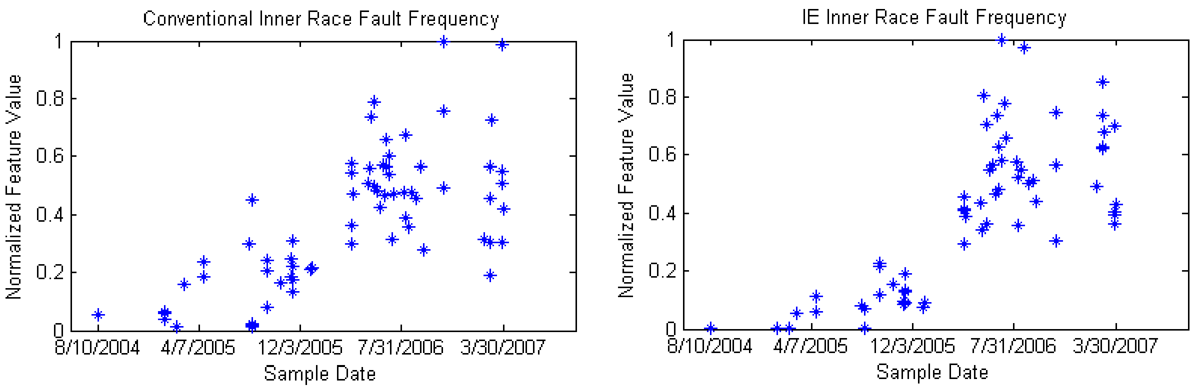

Fig. 6: Inner Race Trends for H-60 Vibration Data.

Surrogate Test Bearing Dataset

The dataset obtained from the Impact test rig provides the opportunity to better demonstrate some of the diagnostic enhancements presented in this paper. This data source has ground truth information that can be used to identify baseline, incipient fault, and progressed fault data. Also, the presence of multiple accelerometers creates the opportunity for sensor fusion techniques.

The Active Band Selection (ABS) algorithm was applied to the bearing vibration data. In Fig. 7 the feature results for the ABS algorithm are presented for a range of potential carrier frequencies. The analysis identified six potential frequencies to use for the center frequency of the ImpactEnergy demodulation process. System knowledge was used to eliminate four of these frequencies that were known to be in regions where noise was likely to distort feature extraction results. The leading candidate of the remaining frequencies, 23.5 kHz, was used for all ImpactEnergy feature extraction.

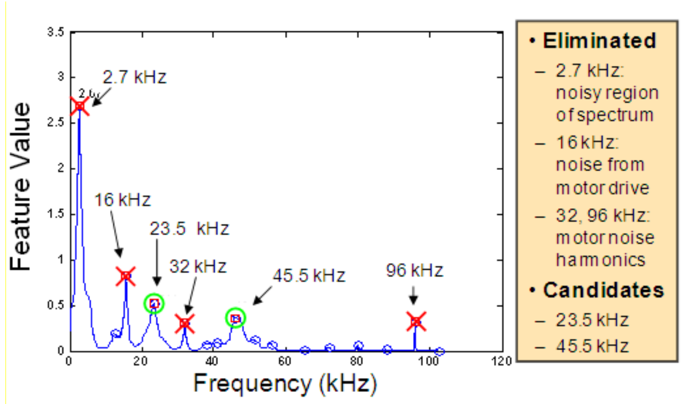

Fig. 7: ABS Feature Results.

In this case, the fault was clearly identified as a spall located on the inner race of the bearing. Therefore, the inner race fault frequency would be expected to be a key piece of evidence for fault detection. Fig. 8 provides the inner race fault feature trends obtained for the conventional and ImpactEnergy spectrums. Again, all feature values are normalized on a 0-1 scale. While the conventional feature provides good indication of the progressed fault condition, the resulting detection threshold results in several cases of false alarms and missed detection. The feature value trend obtained after the signal processing process provides clear separation of the baseline, incipient fault and progressed fault classes. As illustrated in the trend plot, thresholds can be created for this feature that provide fault detection without error as well as a fault severity assessment.

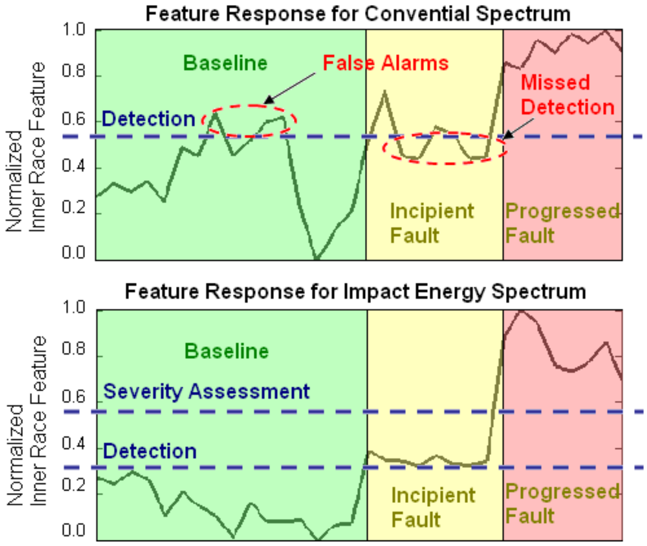

Fig. 8: Effect of IE Processing on Detection.

To further improve the performance of the inner race feature, feature fusion was used to combine the three best performing features into a single health index. Due to the small number of data samples available to refine the fused feature, a simple linear projection was created using principal component analysis (PCA). This technique of linear algebra reduces data dimensionality while retaining the most critical information. The resulting fused feature (Fig. 9) has lower feature variance for each of the three classes than is observed in the inner race feature alone.

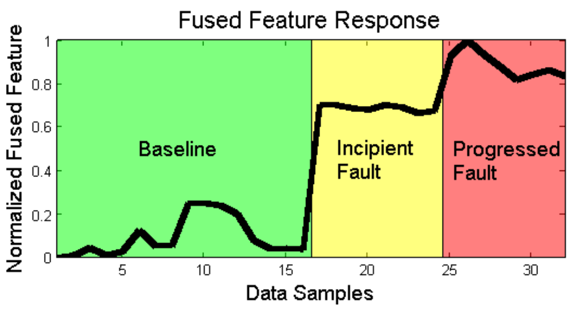

Fig. 9: Fused Feature Trend Plot.

Finally, sensor fusion was attempted to further enhance the fault response of the inner race feature. The bearing test rig collects sensor data in three locations. Two of these measurements are taken in close proximity to the test specimen. The third accelerometer is located far from the test specimen in close proximity to another bearing. It is not expected that this distant accelerometer would provide useful information about subtle faults present in the test bearing. All features presented so far were derived from the radial sensor near the specimen. To demonstrate sensor fusion, three techniques: beamforming, principal component analysis and the SUMPLE algorithm were applied to the time domain data from the two closest accelerometers [9].

Beamforming is a process of concentrating an array of signals (typically sounds) coming from only one particular direction, where signals of the same carrier frequency from other directions can be rejected without the need to reposition or move any receiving sensors [10]. Fig. 10 shows a beamforming procedure that can be implemented for sensor-level fusion.

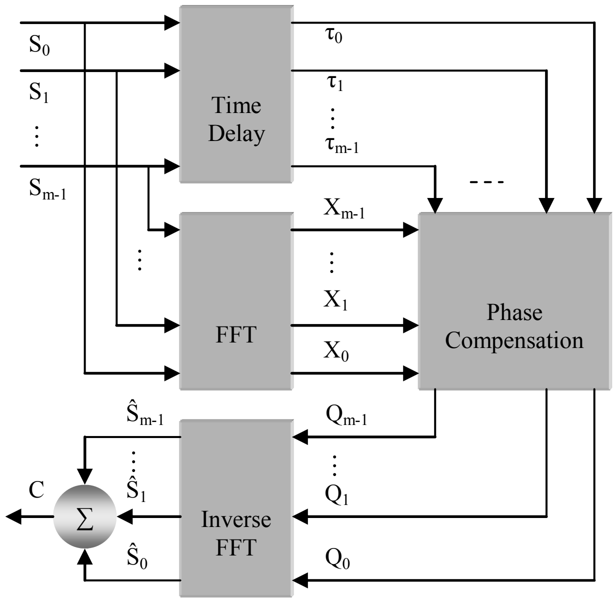

Fig. 10: Beamforming Process.

Principal Component Analysis (PCA) is a well-documented technique of linear algebra that reduces data dimensionality while retaining the most critical information [9]. Lastly, SUMPLE is a digital signal processing algorithm used as a means of combining the outputs of signals from multiple receivers in a large array for the purpose of receiving and increasing the signal-to-noise ratio of a weak signal transmitted by a single distant source [9,11]. The SUMPLE algorithm is illustrated in Fig. 11.

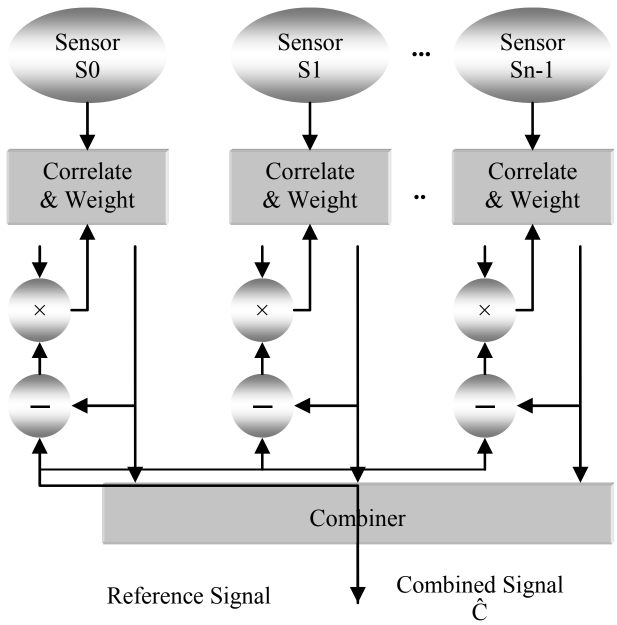

Fig. 11: SUMPLE Algorithm Process.

An example of resulting feature trends obtained from applying each of the three aforementioned fusion techniques are presented in Fig. 12. The inner race feature extracted from the radial sensor only is provided for reference purposes.

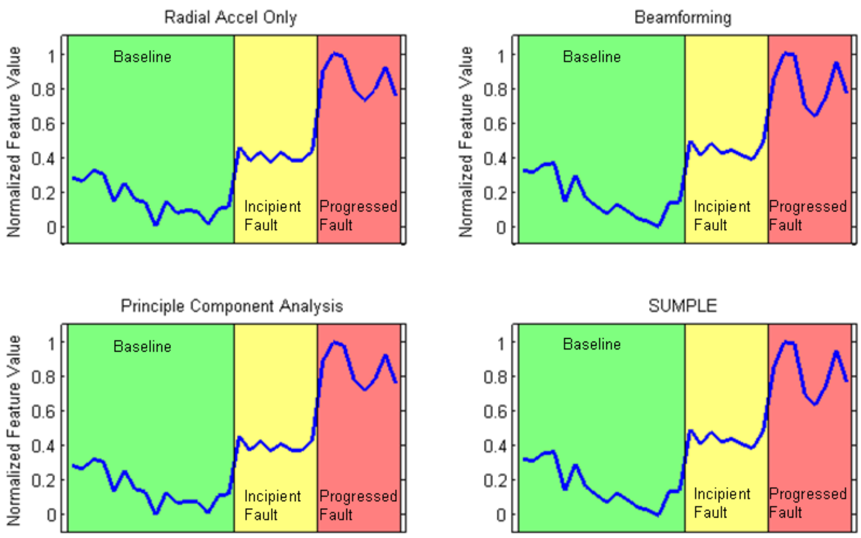

Fig. 12: Inner Race Feature Sensor Fusion Results.

The results show that there was no observed benefit from sensor fusion using any of the three techniques. In this case the information gained from the axial sensor does not provide additional evidence of the fault condition. Note that the beamforming and SUMPLE results display the undesirable effect of a slight increase in feature variance. These results demonstrate that the benefit of sensor fusion is highly dependent on the quality of the information obtained from each individual sensor, and if not done carefully can actually decrease the usefulness of the extracted features.

Use of Diagnostic Enhancements in Support of Prognostics

Fig. 13 depicts an architecture for advanced detection and prognosis. In this architecture, sensor measurements and operational parameters are input in real time. Data is pre-processed to reduce the effect of noise, before computing condition indicators or features indicative of a component's health. Using the enhanced features as described earlier and a model describing the component's degrading state [7], fault detection and failure prognostic algorithms based on particle filtering are applied [8]. Statistical analysis is implemented to evaluate the probability of a fault being present. When the fault is detected with a given confidence level, the prognostic algorithm is activated to predict the remaining useful life (RUL) of the component. This architecture provides not only a convenient compromise between data-driven and model-based techniques, but also the means to evaluate performance with statistical indices [7].

It is possible to provide an example of the effectiveness of this approach using the surrogate bearing data set, where the fault size (ground truth) is available for baseline conditions and different spall sizes. Interpolating available data, we can estimate the expected feature values corresponding to different fault sizes and generate a feature progression curve as shown in Fig. 14.

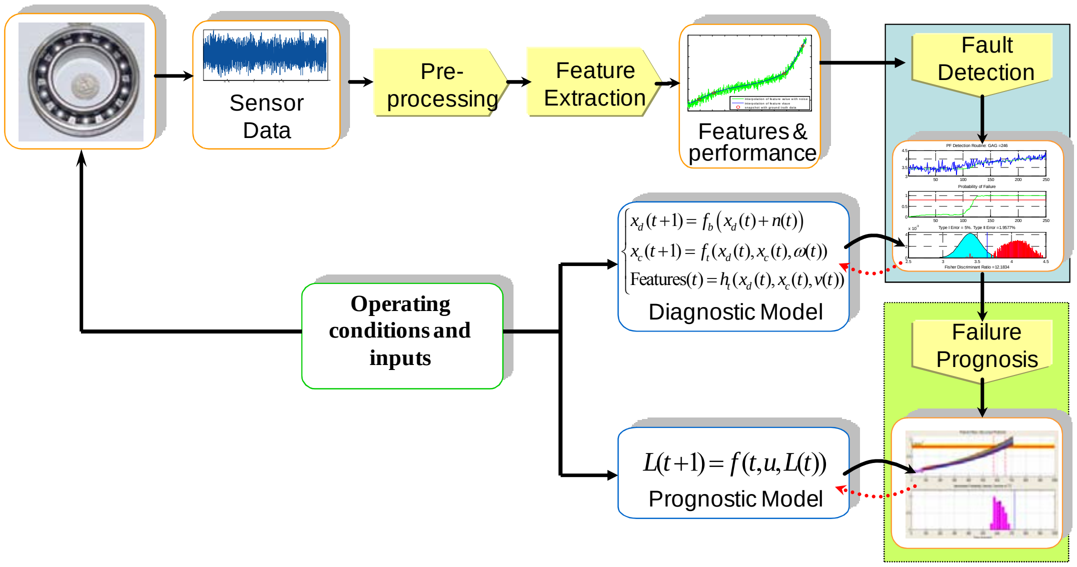

Fig. 13: Proposed architecture for the integration of diagnostics and prognostics.

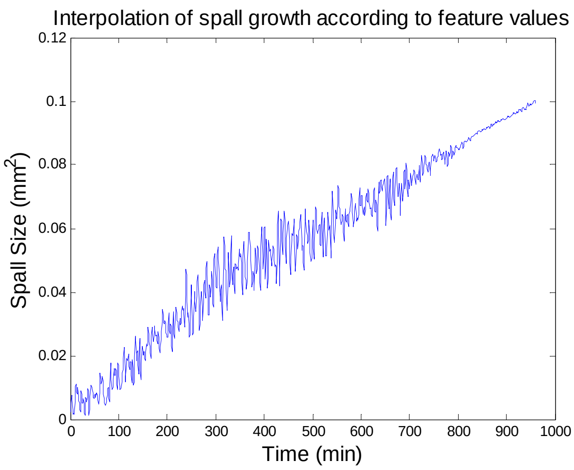

Fig. 14: Interpolation of fault dimension according to feature values.

Since the data is interpolated in terms of minutes, the RUL expectation and 95% confidence interval are also given in minutes. Long-term predictions are provided after fault is detected and using the current estimate for the state pdf as initial condition. Results are depicted in Fig. 15 through Fig. 17.

Fig. 15 shows the minute at which the fault is detected. Before this time instant, the prognostic routines are disabled. As soon as the fault is detected, the pdf estimates at that time are used as the initial conditions for the prognostic routines, as shown in Fig. 16. When a new measurement comes in, the prognostic algorithms will provide an estimate of the remaining useful life. Fig. 17 shows the result at the 350th minute.

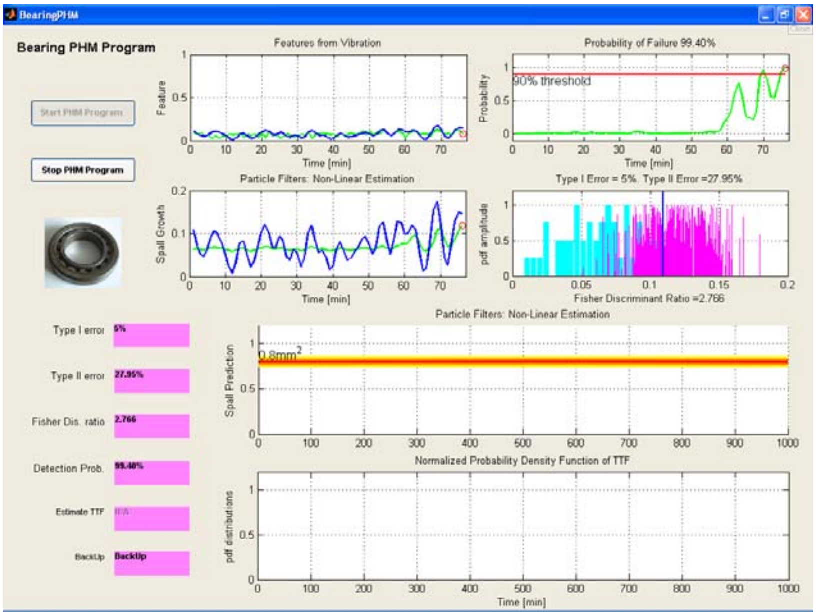

Fig. 15: Diagnostic result when a fault is detected.

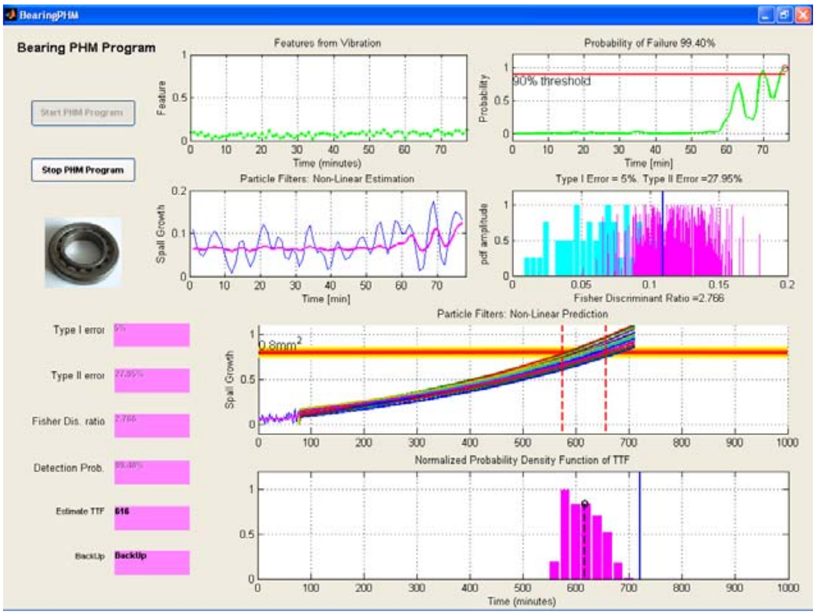

Fig. 16: Initial prognostic estimation right after the fault is first detected.

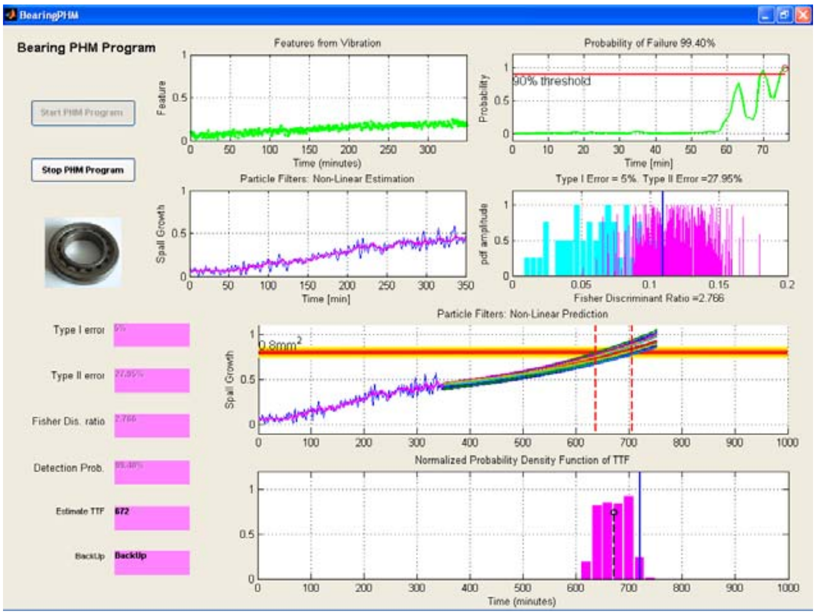

Fig. 17: Failure prognosis at the 350th minute of bearing operation.

Conclusion

This paper shows that enhancements to diagnostic techniques are desirable as well as attainable additions to Digital Source Collectors (DSC), particularly in the case of rotorcraft component monitoring. Enhancements like those presented support CBM efforts primarily in two ways: reduce the sensitivity of diagnostic processes to both signal noise and variations in environmental and operating conditions, and improve the performance of detection systems as well as the task of fault identification (e.g., severity quantification) towards the instantiation of reliable prognostics.

Representative examples, motivated by the interest of the U.S. Army in transitioning from time-based (using TBO definitions) to condition-based maintenance for an H-60 drive train bearing, illustrates the potential benefits of pursuing an integrated approach to diagnostics and prognostics, combining technologies for enhanced data pre-processing, advanced diagnostic-support algorithms, fusion at the feature level, and an adequate framework for false alarm mitigation and uncertainty management. Sensor level fusion techniques did not offer improvements in signal characteristics with the examples used, but the data set was very limited, and this aspect of the work is ongoing. A series of tests on rotorcraft drive train bearings with varying fault severities and under multiple, though realistic, operating conditions are currently being planned, with the objective of providing additional data to demonstrate the effectiveness of the proposed data processing techniques and assessing the performance of related diagnostic and prognostic algorithms, with aim to support the U.S. Army's maintenance objectives by providing technologies that make detection systems more robust, allow for the implementation of prognostics, and extend the useful life of drive train components.

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