ABSTRACT

Title of Document:	ROLE OF ON-BOARD SENSORS IN REMAINING LIFE PROGNOSTIC ALGORITHM DEVELOPMENT FOR SELECTED ASSEMBLIES AS INPUT TO A HEALTH AND USAGE MONITORING SYSTEM FOR MILITARY GROUND VEHICLES
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Improved reliability of military ground vehicle systems is often in direct conflict with increased functionality and performance. Health and Usage Monitoring Systems or HUMS are being developed to address this issue. HUMS can be practically defined as a system of sensors, processors and algorithms that give an indication of remaining component life. Fatigue of metal components is a common failure mode on military vehicles, and failures of this type have a major effect on vehicle reliability and availability. The purpose of this research is to develop the methods and algorithms necessary for applying HUMS and remaining life prognostics to metal fatigue on a military wheeled vehicle.

A range of models were developed and fidelity of the models was shown to be correlated with computational complexity. Simplistic models based on feature

recognition had the least potential for accurate fatigue damage predictions while high fidelity physics-based models had the most potential. Recommendations for the information needed to select the most appropriate model for a component and optimize the effect on vehicle reliability and availability were discussed. Methods for identifying the set of instrumentation that could reasonably be used as part of a HUMS and techniques for selecting the instrumentation that provides inputs for metal fatigue damage models were evaluated. Techniques for identifying critical data and instrumentation were also described. The methods and algorithms developed were demonstrated for a variety of components on a military wheeled vehicle, and validation was performed by comparing the results of the remaining life prognostics with those from high fidelity physics of failure models.

The processes developed could be easily adapted to other platforms including commercial fleets of vehicles or aircraft. These algorithms and techniques provide potential for improving reliability and availability, but it should be noted that other methods may be more appropriate depending on the specific vehicle and failure mode. Significant work remains to implement HUMS technologies on a military wheeled vehicle, but increasing reliability and availability is a worthy goal.

ROLE OF ON-BOARD SENSORS IN REMAINING LIFE PROGNOSTIC ALGORITHM DEVELOPMENT FOR SELECTED ASSEMBLIES AS INPUT TO A HEALTH AND USAGE MONITORING SYSTEM FOR MILITARY GROUND VEHICLES

By

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Chapter 1: Introduction

A current goal in the military is to increase the reliability of vehicle systems to mitigate life cycle cost and improve operational availability and readiness. In addition, new requirements for functionality and performance are resulting in increasingly complex vehicle systems. To address these conflicting issues, novel ways of improving reliability and readiness are needed. One method being examined by the Department of Defense is the inclusion of a Health and Usage Monitoring System (HUMS) within a vehicle platform. HUMS are a system of sensors, processors and algorithms that give an indication of remaining component life. These systems indicate the usage of an individual vehicle and the effect of environmental factors on specific components. Processed data informs operators, maintainers, and mission planning personnel which components should be serviced or have the lowest probability of failure during a mission. The data also characterizes vehicle usage. With good management, this information increases availability and reliability, while decreasing overall maintenance and system costs.

1.1 Problem Statement

In a fiscally conscious environment, reliability is a critical consideration in the design and manufacture of products. For many items designed to be used over a long time span, operation and support represents a larger proportion of the total cost than procurement. Reliability directly affects the logistics burden associated with a particular piece of equipment and is a major driver for operations and support cost. This is the case for many military vehicles, but military vehicle designers have additional incentive to design reliable equipment. Failure of components or subsystems results in inconvenience for civilian users of products, but soldier safety and effectiveness are often dependent on the operability and performance of their vehicles. Maintaining operation of the critical functions and subsystems is essential to the completion of the difficult and dangerous missions assigned to military personnel.

Even though reliability is typically assigned a high level of importance during the development and selection of Army equipment, the Government Accountability Office reports that some major systems still have reliability issues. In order to obtain the desired improvements in reliability through technologies such as HUMS, methods and algorithms tailored to a ground vehicle need to be developed. Ground vehicles are a difficult application for HUMS due to the large number of unique components, complex loading and usage, and relatively low cost. Methods to track the environmental effects on components need to be developed for the major modes of failure which can be addressed by HUMS. Many attributes of a HUMS, including the integration process, number of components monitored, sensor type and placement, failure modes, and recording and reporting methods, all need to be balanced with the cost and potential for reliability improvements for the most appropriate methods to be selected.

1.2 Background and Motivation

One of the major modes of failure for many military ground vehicle components is metal fatigue. Input loads on critical components can come from a variety of sources. Temperature fluctuation from extreme environments or power source generated heat, vibration from terrain or rotating components and shock loading from enemy attacks, weapon firing or even an inexperienced driver hitting an obstacle can all contribute to fatigue of critical components. In addition, there is reason to push the standards typically used in design. There is a general desire to produce lighter vehicles to ease transport, provide improved mobility, increase range, and save fuel. Often the only practical way to decrease weight is through reduction in design margins and safety factors. Ground vehicles are also becoming increasingly complex as new technologies become available which increase performance. Precision guidance, advanced communications, active suspensions, automation, and robotics have all been used to reduce the number of soldiers in harms way and maximize the potential of the soldiers who are in harms way. Incorporation of HUMS in vehicles could allow for increases in complexity and reductions in design margins while maintaining or improving vehicle reliability.

Typically HUMS are divided into two major categories, diagnostic and prognostic. Diagnostic HUMS are those systems that detect the presence of a fault, based on signs or symptoms. Comparison of sensor outputs to those from previous states or known healthy components provides warning of when failure is incipient or has recently occurred. A major challenge for diagnostic HUMS is the identification and application of sensors that will provide a consistent, accurate indication of component health. In addition, the natural variation between responses of individual components can be significant enough to make it extremely difficult to provide warning of failure early enough to be useful. Finally, this category of HUMS is reliant on the damage tolerance of the components monitored. In order for sensor output to change, the physical or structural properties need to be altered before an indication would be available. Components with limited damage tolerance would only provide a short time between initial indications that could be detected by a diagnostic HUMS and final failure. Application of diagnostic HUMS to components with low damage tolerance would result in very limited improvement to overall system reliability.

Since many mechanical components within a vehicle are damage intolerant, or do not undergo “graceful failure”, prognostic HUMS is a more promising candidate. Prognostic HUMS is based upon monitoring damage on a component and making predictions of remaining life. Typically, environmental variables such as load and temperature are monitored and recorded for a particular component. These are variables used to determine the damage accumulated on the component. Predictions can be made as to the remaining life of the component and maintenance can be prioritized and scheduled around usage. Furthermore, readiness can be improved by utilization of vehicles within a fleet that have substantial remaining life. Some of the difficulties with prognostic HUMS include the fact that the entire load history of a particular component needs to be known to make accurate forecasts of remaining life. In addition, fatigue calculation is a statistical process which can vary significantly between components. Great quantities of detailed information, including material properties, material variations and failure mechanisms of the individual component, may be needed to implement complex remaining life prognostics models.

Methods for the calculation of fatigue damage are numerous, but selection of appropriate algorithms that provide sufficient accuracy within the constraints of a

HUMS devised for use in a ground vehicle system provides a significant challenge. An analysis of the potential solutions is needed to indicate reasonable algorithms that are appropriate for use in a prognostic HUMS applied to ground vehicle systems and appropriate algorithms for individual failure modes.

1.3 Approach

Much work has been done to develop HUMS technology and remaining life prognostics. Groundwork has been laid through the development of custom HUMS for expensive systems operated over long time frames, but this approach is too costly and time consuming to be justifiable for many applications including military ground vehicles. Simple algorithms are needed that provide estimates of remaining life for critical components to meet the reliability goals set for military vehicles. Accuracy of predictions needs to be retained such that false alarm rates are minimized and the system justifies the additional cost. It is the goal of this research to develop the methods and algorithms necessary for applying HUMS and remaining life prognostics to a variety of components within a wheeled vehicle. In addition, sensor selection and evaluation will be studied for use in HUMS models of varying complexity. The focus of this research will be military ground vehicles, but the general principles could be applied to many other platforms. Elements could be easily adapted for use on aircraft or commercial fleets of vehicles. Complexity of the application, criticality of the component, number of failure modes, and available time will be discussed based on the type and complexity of HUMS models developed.

Validation will be performed by comparing the results of the HUMS remaining life prognostics with results from a high fidelity physics of failure model

(See Appendix A) on test courses not used during algorithm development and training. Ideally, the predictions would be validated with failure data, but the time to failure is too lengthy on target components for this approach to be practical. Another option would be the use of accelerated testing to validate results. Full vehicle tests would be required in order to obtain the complete set of input parameters necessary, and many components would need to be tested to get a measure of the statistical spread of failures. Even accelerated testing on a limited number of vehicles is far too expensive to perform. The accuracy of the HUMS prognostics is best measured against well known physics of failure analyses. However, any inaccuracy in the physics of failure analyses will be propagated to the HUMS prognosis. The most accurate HUMS estimate of remaining life could only be expected to provide an estimate of similar quality as that of the physics of failure analysis used to train it.

1.4 Overview of Thesis

In order to evaluate the practicality of application for different HUMS and remaining life prognostics algorithms, it was necessary to develop models with a range of fidelity and computational complexity that could be applied on a wide variety of fatigue damage sensitive components. A review of the literature on current HUMS and the technology supporting their development is detailed in Chapter 2. Chapter 3 is an article, formatted for publication and currently in press in Microelectronics Reliability, which defines a simplistic set of terrain identification algorithms to determine fatigue damage for electronics whose primary method of loading is terrain induced vibration (Heine 2007). Chapter 4 contains a paper formatted for publication that provides similar remaining life prognostics and HUMS algorithms for a mechanical component subject to terrain induced vibration and is under review with the Journal of the Institute of Environmental Sciences and Technology (IEST). Chapter 5 defines a set of more computationally complex algorithms that use measured acceleration to predict strain and fatigue damage. These algorithms are suitable for special load cases where acceleration waveforms are similar to strain. Chapter 5 is also presented identically to the article format submitted to the Journal of the IEST. Chapter 6 develops methods for identifying good indicators of strain from a wide variety of sensor data for a multiaxial load case. Physics based subsystem models are also developed and compared based on the improvement in fatigue damage prediction capability. Chapter 6 was also formatted as an article for release in a technical journal that is yet to be determined. In each of the Chapters 3-6, a sample component was selected from a military wheeled vehicle to demonstrate the applicability of the methods and algorithms developed. Chapter 7 provides a summary of the results, lessons learned and recommendations for future work in the field of remaining life prognostics and HUMS.

Chapter 2: HUMS Technology

Significant challenges exist in the development of HUMS for military ground vehicles, which are typically made up of a large number of unique components, have complex loading and usage profiles, and are produced at a relatively low cost. Determining the methods and algorithms appropriate for application to a military ground vehicle HUMS, requires a review of previous applications and technologies.

2.1 Current HUMS Applications

The concept of HUMS is not a new one. However, the costs associated with development and application, along with the detailed knowledge necessary to perform health and usage monitoring, has limited application to only those very expensive systems that are operated over long time spans. Much of the literature is written for fixed wing aircraft or helicopter applications. Currently, a HUMS is planned for rotating components including the lift fan shaft of the Joint Strike Fighter F-35 ("Prognostics..." 2004). Bodden et al. (2006) describes an optimization of a HUMS for an unmanned aerial vehicle in terms of reliability and availability. A HUMS was also developed for a Boeing 757 landing gear and the effects of an expert system on maintenance were discussed in Woodard et al. (2004). Martin et al. (1999) describe a HUMS for the V-22 Osprey that performs pattern recognition to track loading profiles on individual components. This system monitors and records vibration data, structural inputs, and engine diagnostic information. Teal et al. (1997) discussed the application of a HUMS on the CH-47D Chinook helicopter that tracks usage and monitors events where parameters exceed expected values. The Chinook system was shown to significantly decrease the time necessary to balance and adjust the dual rotors. Application of an aftermarket HUMS to helicopters and integration with the existing flight data recording and cockpit voice systems is discussed by Gordon (1991).

Other applications of HUMS discussed in the literature are an advanced artillery system (Araiza 2002), manufacturing and power plants (Li 1995 and Jarrell 2006, respectively), and an elevator system (Yan 2005). Schuster et al. (2004) created a diagnostic technique designed primarily for multi-processor computer servers. Vichare et al. (2006) described HUMS as applied to the field of electronics and discussed four promising technologies. These included built-in-test, fuses and canary devices, monitoring and reasoning of failure precursors, and models of accumulated damage based on life cycle loads.

While HUMS have been developed and used on a wide variety of platforms, a systematic approach for the application of a HUMS in general is not readily available. Much of the work, such as the description by Barone et al. (2007) of a process for creating an on-board diagnostic for oxygen sensors in an automotive environment, is application specific or focused on diagnostic HUMS for rotating components. Greitzer et al. (2002) authored one of the few articles specifically addressing a military ground vehicle. The ground vehicle described was an M1 Abrams tank and the HUMS was focused on the assessment of a turbine engine, bearing many similarities to those used in aircraft. This work utilized a diagnostic HUMS to monitor the rotating components for precursors to failure. Some limited discussion was provided regarding the application of a similar system to a diesel engine repower effort. Portions of the lessons learned, technology, processes and techniques developed for use with these diagnostic HUMS can be applied to a generalized prognostic HUMS. First, it is necessary to describe the envisioned requirements for such a system designed for a military ground vehicle.

A HUMS applied to a military ground vehicle system requires a number of modifications. First, the sensors used need to be sufficiently reliable such that the HUMS do not contribute significantly to the total platform reliability. In order to improve the overall system reliability, it is essential that the entire HUMS are rugged and not prone to failure. Rough terrain, extreme temperature fluctuations, dust and large fluctuations in humidity are common occurrences on military vehicle systems, and can be damaging to the entire HUMS. Sensors are especially sensitive to these effects. Many of the sensors available for use in aircraft, plant, or electronic applications would not survive long in the field environment of a military ground vehicle system. Constant replacement or calibration would counter the goals of increasing durability and readiness, while decreasing the logistics footprint of the platform. To minimize these environmental hazards, ruggedized instrumentation designed into the platform is preferred.

Compared to many of the previous mentioned applications of HUMS, the development and unit cost need to be much less. Cost of a military ground vehicle system is often several orders of magnitude less than aircraft, so expenditures need to be reduced by a relative proportion. In addition, cost of the HUMS can not be a significant portion of the vehicle cost. Redesign of components or replacement of the entire system may be preferable if the HUMS is cost prohibitive.

One of the key elements for the application of a HUMS system to a ground vehicle is that the system perform computation on-board the vehicle. Data required for the accurate calculation of fatigue, in addition to the error-checking algorithms and digitization, requires significant computational capabilities. However, the bandwidth required for continuous raw data transfer or the storage necessary for long missions makes off-vehicle processing unfeasible. As computing power becomes more compact and less expensive, processing capabilities onboard continue to improve. This is a major reason prognostic HUMS is becoming feasible for less expensive systems such as military vehicles.

2.2 HUMS Functions

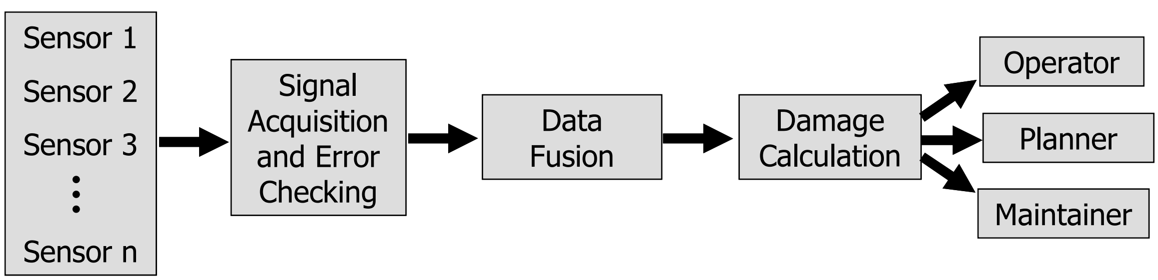

Figure 2.1 HUMS functional view

Figure 2.1 provides a functional view of a prognostic HUMS. Signals related to different failure modes are measured by sensors at various locations on the vehicle. The signals are converted into a digital data stream at the sensor or a central processing location. Algorithms are utilized to check the validity of the data and address dead channels, spikes, drift, offset, and clipped data. The data streams from various channels are then combined to form useful indications of environmental effects on a specific component. A simplified physics of failure model is used to analyze the environmental effects, compute the damage accumulated on the component, and provide predictions of life remaining. This condensed information is made available to the maintainers, operators, and mission planners. One weakness of a model such as this is that small errors from each of the steps can contribute to large overall error at the system level. Significant error can result in poor HUMS predictions. Thus, the selection of components and magnitude of the error contained within the calculation is critical to the success of the HUMS.

The first functional piece of a HUMS is the suite of sensors. Significant work has been published regarding the development of sensing technology for HUMS. Ellerbrock et al. (1999) demonstrated the use of Uni-Axial Strain Transducers (UASTs) to measure loading on helicopter blades. These UASTs monitor strain by measuring the length between a stationary foot and a moveable foot that contacts an array of field sensors. This sensor is claimed to be much more robust than common, foil-type strain gauges. A contactless slip ring was also demonstrated that could be used for collecting of information on rotating components. Northwang et al. (2006) describes the integration of piezoelectric sensors within structural titanium as an input for both prognostic and diagnostic HUMS. Piezoelectric sensors affixed to a structural member can be used to indicate loading when voltage is monitored or to generate a vibration for structural health monitoring when time varying voltage is applied. Wilson (1997) suggests that microelectromechanical systems (MEMS) are critical to the future of HUMS. MEMS are promising due to the versatility of devices, the microscopic size, and low power consumption. However, much development needs to be accomplished before MEMS will be available and inexpensive enough for military vehicle platforms.

Systems of sensors often contain overlap. If the sensors are not totally independent, there exists some level of cooperative, complimentary or competitive information in the data stream. Cooperative sensors are defined as those that work together to provide useful information. Complimentary sensors provide a more complete view of the signal, and competitive sensors provide redundancy (Roemer et al. 2001.) Schuster et al. (2004) makes use of the competitive nature of sensor arrays. A sinusoidal excitation technique is described that can be used for estimation of signals if a critical measurement is not available. The sinusoidal excitation technique concentrates effort on a limited number of points in the frequency domain where critical parameters are correlated. Thus, if a critical signal is lost, not able to be measured, or irreparably damaged, it can be estimated from a correlated signal. This technology would be very useful in improving the reliability of a HUMS.

Another method to improve the availability of sensors is constant monitoring and rapid replacement of sensors when faults are detected. This minimizes the time that a system is not monitored and improves the accuracy of both prognostic and diagnostic HUMS. Ng et al. (2006) developed a health monitoring system for actuators and sensors on a passenger vehicle. This system is based on analytical redundancy or the ability to predict patterns and identify faults based on residuals.

Use of sensors already integrated within the vehicle is an ideal source from which to estimate input parameters. These sensors typically have high reliability due to their use in other vehicle subsystems and the cost of integrating them within the

HUMS is minimal compared to the cost of adding an additional sensor. Signals from many of the integrated sensors are available through a data bus and can be easily monitored. Sensors such as accelerometers and GPS units are robust, easy to apply and make a good alternative source if the integrated sensors do not provide data suitable for HUMS.

The second functional piece of a HUMS is the signal acquisition box and error checking algorithms. Signal acquisition technology is commercially available and many of the companies that provide equipment to the test industry have equipment that provide basic storage, telemetry, filtering, and processing capabilities within a single box. Trammel et al. (1997) describes a HUMS designed for aircraft that was integrated with the crash survivable cockpit voice and flight data recording system. Integration with other systems would be of benefit to the military vehicle application by reducing unnecessarily repeated functions, minimizing space and power requirements and reducing the risk of tampering. For various reasons, users may not want vehicle usage data recorded. A highly integrated system would also be much less likely to be disturbed than a stand-alone, easily accessible counterpart.

Error checking algorithms are a source of difficulty in any HUMS. Data spikes, drift, offset and clipping are all on the common errors when dealing with measured data. While a test engineer has ample time, experience, and specialized tools to deal with these errors, a HUMS designed for a vehicle system must be largely hands-off. Evans (2002) described recording the necessary data and displaying questionable data segments to off-vehicle personnel in a system designed for helicopters. Recording all of the measured data or only questionable segments is not feasible for most military ground vehicle platforms, considering that a mission may be weeks long and the cost for qualified personnel to study the data would be high. Data checking algorithms would be more appropriate and greatly reduce the inaccuracy of the data. Hadden et al. (1983) developed limits for reasonable data. Data that fell outside these limits were considered absurd and invalid. Error was then bracketed by developing a regression line of all data and rejecting points outside a fixed fraction of the magnitude of error residue, outside a fixed fraction based on the magnitude of the parameter, or outside a limit based on calculated variance. Other statistical methods are available to detect errors and in some cases estimate actual values. Nonetheless, error within the data stream can be a critical issue and severely limit the types of sensors and the parameters measured.

The third functional step of a HUMS is data fusion. Measured data alone does not usually provide the inputs necessary to feed a failure model. Some knowledge of the system and surroundings is required to convert the measured data into useful inputs. Often this involves the combination or conversion of multiple data streams. Zhang et al. (2003) describes different fusion architectures and developed a criterion for assessment of the value of the different architectures in relationship to diagnostic or prognostic capabilities. Roemer et al. (2001) compares feature and time stream fusion techniques as applied to a gas turbine. Neural network fusion was successfully used for diagnostics and sensor validation. Hunt et al. (2000) utilized an event recognition device to match significant structural events to 17,000 known load situations as a function of time. These finite element generated stress maps were used as direct inputs to fatigue and overstress models. Bechoefer et al. (2004) utilized a statistical approach to develop a health indicator that tracks likelihood for multiple modes of failure in helicopter systems. These fusion techniques convert the data received into useful information used to feed a failure model. Gandhi et al. (2007) successfully demonstrated fusion of video and strain data to identify and track size and weight of vehicles crossing a bridge as part of a prognostic HUMS.

Many different types of failure models exist with varying accuracy and computational effort. One set of models already developed are phenomenological or statistics based models. Phenomenological or statistics based models monitor and accumulate data that can be correlated to usage of individual components. Data are kept throughout the life of the component and compared to known or predicted failure distributions. When the usage monitored reaches an unacceptable level of risk, warning of potential failure is provided. Ray et al. (1996) suggest a statistical approach to crack growth for use in HUMS applications. A stochastic model was developed and initial results were shown to be accurate for 2043-T3 aluminum. Mourna and Steffen (2006) investigated the use of a probabilistic neural network and surface response models as ways to characterize damage in the vertical fin of an unmanned aerial vehicle.

If strain or loading is monitored at critical locations throughout the life cycle of individual components, a second type of model that calculates fatigue damage accumulation can be utilized. Miner (1945) suggested a model that could be used to address fatigue in a variety of components and materials. When used in conjunction with either the Basquin or Coffin-Manson equations and a mean stress correction method, such as the Morrow or Smith-Watson-Topper method, Miner’s model is capable of predicting remaining life of a component under variable mean and amplitude loading. Other similar models have attempted to address known deficiencies in Miner's formulation such as nonlinearity and load level interaction (Fackler 1972). More computationally complicated models, such as the Wang and Brown model (1993), address multiaxiality issues often associated with mechanical components in the automotive environment. These models iteratively search for a critical plane within the failure region and sum the damage accumulated at this critical plane. Li et al. (1995) utilized a continuous-time fatigue model based on Coffin-Manson and Basquin relationships for use on a HUMS applied to critical components at a plant.

A third set of models that track crack propagation, such as one based on Paris' Law from fracture mechanics and discussed in Veers et al. (1989) or Pilkey (1994), is also useful in predicting life of a component. A related technique was suggested by Wakha et al. (2003) for application to HUMS. Cracks were detected and their growth monitored through the use of a mesh of dual stiffness/energy sensors. This technique was based on Eshelby's equivalent inclusion method and compared far field stress levels with those near inclusions. Experimental verification was performed for aluminum, brass and acrylic, and showed accurate predictions for the aluminum samples.

To utilize any of the models in a prognostics application, issues specific to the component such as the acceptable cost, failure mechanism, and the method of measurement must be addressed. Many structural components have strains that are multiaxial in nature, but maintaining the complete time history and iteratively searching for a critical plane is likely to be too computationally intensive for use in an automotive-based prognostic system. Conversely, for a phenomenological-based model, tracking usage based on parameters not directly related to fatigue will likely result in inaccurate predictions. To make use of predictions with less accuracy, very early repair or replacement is necessary for acceptable levels of risk. A combined approach of using Miner's model for crack initiation and a simplified fracture mechanics model for crack propagation is a promising candidate. This approach is computationally simple and the individual models can be used in conjunction with data reduction techniques such as rainflow cycle counting, histogramming, and racetracking. In addition, this approach has the added benefit of providing logical inspection intervals based on the crack propagation period for the monitored component.

Finally, the delivery of information to the personnel using or monitoring the equipment requires consideration. Simply determining which personnel should have access to the information is important. Moreover, estimating remaining component life helps maintainers schedule maintenance and focus inspections. Accurate usage data is essential information to future vehicle design teams. Mission planners could use projections of the likelihood of failure to develop probabilities of success for a given operation and select vehicles and units to utilize. Information such as immanency of failure is useful to the operator if reliable and not too distracting. Evans (2002), as part of the Flight Deck Health Monitoring Indications Working Group, studied this issue in terms of incidents versus false alarm rates for a helicopter system. Alarms for critical components may result in ditching the aircraft which contains high risk. Based on this study, it was determined that an alarm for failure should not be introduced until the false alarm rates were extremely low. Information as to component failure in military ground vehicles are less likely to result in a dangerous activity, but too much information is an issue for vehicle operators. The type and quantity of information provided from a HUMS also needs to be selected carefully. Martin et al. (1999) proposed a system for the V-22 that provided maneuvers performed and exposure time based on pattern recognition on-board. Data not fitting a known pattern was recorded and provided to maintenance personnel daily. The combination of the two data sets allowed the maintenance personnel to make more accurate assessments of fatigue and improve maneuver recognition software.

2.3 Implementation of HUMS in a Military Vehicle Life Cycle

In order for HUMS to have the maximum effect on a vehicle's reliability, the HUMS should be integrated into the vehicles design at an early stage. Figure 2.2 illustrates the incorporation of a HUMS into a military vehicle life cycle. Most military vehicles are already instrumented with various sensors to for driver feedback, to identify faults, or as a diagnostic tool when maintenance is performed. Ideally, a HUMS designed for military vehicles would have access to these sensors, as well as a set of sensors specifically implemented to monitor the usage of subsections of the vehicle. Sensors developed and integrated during the design phase of the vehicle can be more cheaply implemented than those added after the design is finalized. Sensors and communication links in wired or wireless forms have increased durability and survivability, while providing more accurate measures when added during the design phase.

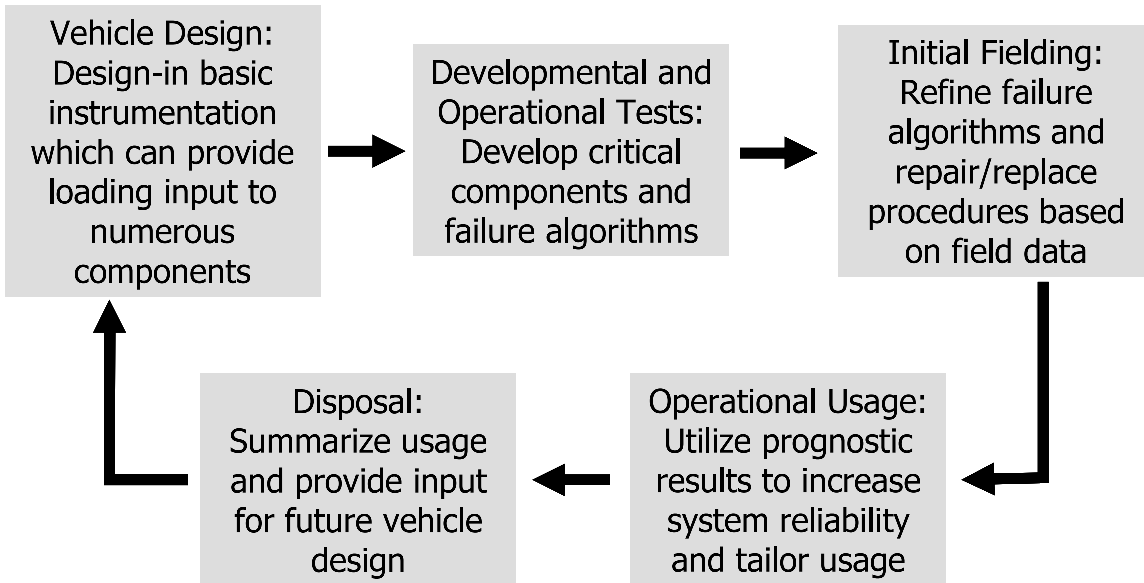

Figure 2.2 HUMS in military vehicle life cycle

Military vehicles are required by law to undergo significant developmental and operational tests. During these tests, the instrumented data could be collected in raw form. As failures modes are discovered, data from the designed-in sensors could be related to the individual failure modes. Algorithms could then be developed to evaluate accumulated damage on specific components and refine maintenance schedules based on HUMS predictions. As the initial vehicles are fielded, actual usage data could be collected and used to refine the prognostic capability of a HUMS. Failure reports and parts utilized could be used to further refine statistics of individual components. As more vehicles are built and phased into operations, the HUMS would improve overall readiness and reliability, while providing information regarding usage. One of the most difficult aspects of vehicle design is to estimate usage profiles. A HUMS system applied to a military vehicle would help to address this issue for future vehicle systems. As one vehicle life cycle was entering the disposal phase, usage data could be compiled and used to provide better estimates of the environment and way in which future vehicles will be operated.

Based on this vision of the incorporation of a HUMS in a military vehicle life cycle, several major issues need to be addressed to develop remaining life prognostics for fatigue damage susceptible components. Strain measurements are desirable as an input to fatigue damage estimation models. However, the common method of measuring strain with adhesively bonded, electric resistance wire strain gauges is fraught with difficulties. This type of strain gauge is sensitive to temperature variations, and bonding can be an issue if the gauge is expected to last the life of the component. A preferable approach would be to use more rugged sensors to predict strain on the critical component. Recommendations for the type and placement of sensors that may be useful for a variety of components are essential for making fatigue-based remaining life prognostic predictions.

For many modern military vehicles, the combination of integrated and add-on sensors make a large pool of candidates available for use in a HUMS, but the best indicators of strain are not be clearly identifiable. A method is needed to identify and select sensors that provide inputs suitable for fatigue damage models. Failure locations and mechanisms are not generally known during the design phase. For failure mechanisms that are discovered early in the design phase, it would be more economical to redesign the component to eliminate the defect. If a deficiency in the design goes undiscovered till testing or fielding stages, it becomes much more expensive if not impossible to correct. A method to evaluate the sensors available when coupled with a failure mode analysis and limited instrumented testing, would provide information as to whether the current sensor suite was sufficient to track the environmental or usage inputs that caused the failure. If the sensors did not track the root cause of failure or provide adequate fidelity to track all the failure modes, additional sensors could be evaluated and added to the platform. This method to evaluate sensor potential would be essential to meet the overall goals of keeping HUMS development times down and system cost minimal.

Another issue is the lack of algorithms appropriate for the synthesis of sensor outputs to form a suitable input for fatigue models applied to military wheeled vehicles. Synthesis of sensor output is necessary because the data required to perform fatigue calculations are often not easily measurable. Direct sensor output is not typically of the correct form or must be combined with vehicle subsystem characteristics to provide an accurate estimate of fatigue damage accumulated. Thus, it is critical to have simple algorithms for the synthesis of sensor outputs to minimize the cost and time required for development of a HUMS.

Synthesis of sensor information depends on the type of fatigue model selected. Figure 2.3 illustrates a spectrum of complexity for data synthesis and fatigue models. The simplest models would utilize a feature recognition technique to identify terrain or usage conditions and assign damage for time exposed. More complicated models would measure or predict strain at a critical location and calculate fatigue damage through a rainflow cycle counting and Basquin’s equation or a fracture mechanics approach. The highest fidelity model would utilize a detailed physics model that accounts for all the individual loads applied to a component. Simplified subsystem models would be used to calculate the loading for a component, and a high fidelity fatigue model would be used to calculate damage accumulated and life remaining. As the number of monitored elements grow it would become necessary to evaluate tradeoffs between cost of the HUMS, level of fidelity necessary to provide accurate estimates, and number of components monitored. A method to determine the fidelity necessary to predict damage would be integral to keeping production costs for the HUMS reasonable.

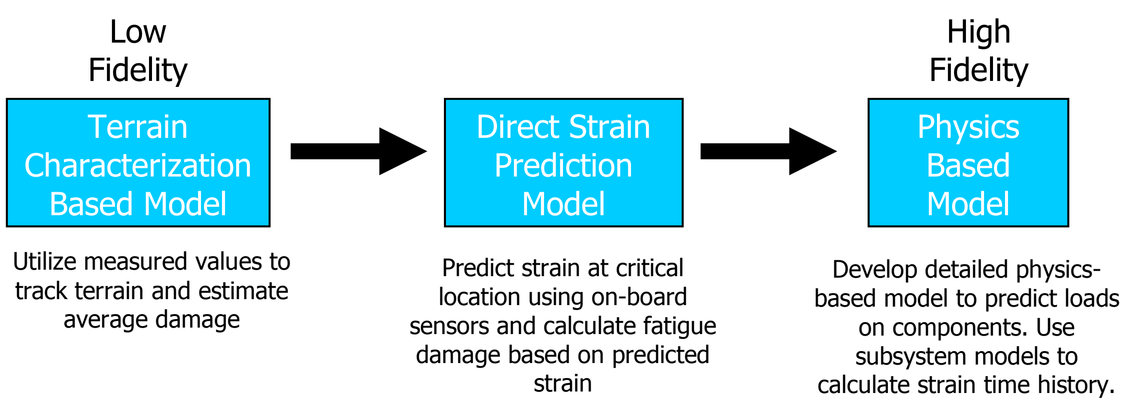

Figure 2.3 HUMS level of fidelity

2.4 Summary

Significant challenges exist for utilizing HUMS technology on a military ground vehicle. The cost during development and implementation and detailed knowledge necessary to perform health and usage monitoring has limited previous applications to very expensive systems operated over long time spans. Algorithms and methodologies for application must be developed for an inexpensive system with complex loading such as a military ground vehicle. Chapters 3 and 4 define a simplistic set of terrain identification algorithms to determine fatigue damage for electronics and mechanical components, respectively, whose primary method of loading is terrain induced vibration. Chapter 5 contains algorithms and application methods for use of measured acceleration to predict strain and fatigue damage. Chapter 6 contains a method for identifying indicators of strain and algorithms appropriate for a multiaxial case. Finally Chapter 7 addresses the lessons learned and conclusions that can be drawn based on the comparison of the models.

Chapter 3: Terrain Identification for Electronics

In order to apply a HUMS to electronics on a military ground vehicle, simplified algorithms that drive terrain exposure from a basic set of sensors and estimate fatigue damage accumulated on components whose loading comes primarily from terrain have been developed. Various inputs and statistical parameters are evaluated for this model based on accuracy of terrain identification and quality of fatigue prediction. The remainder of the material in Chapter 3 is presented as it was formatted for publication in Microelectronics Reliability (Heine 2007) and contains repeated background information. To avoid repeated information, readers should skip to section 3.2.

3.1 Background

Reliability of military vehicle systems is being driven upward to mitigate life cycle cost and improve operational availability and readiness. New requirements for functionality and performance are resulting in increasingly complex vehicle systems. In order to address these conflicting issues, novel ways to improve reliability and readiness are needed. One method that is favored in the Department of Defense is the inclusion of a Health and Usage Monitoring System or HUMS within a vehicle platform. HUMS can be practically defined as a system of sensors, processors and algorithms that give an indication of remaining component life. These systems provide an indication of the usage of an individual vehicle and the effect of the environmental factors on specific monitored components. The resulting data is processed and provides information to operators, maintainers, and mission planning personnel as to which components should be serviced, which vehicles have the lowest probability of failure during a mission, and what the past usage of the vehicle has been. With good management, this information can be used to increase availability and reliability, while decreasing overall maintenance and system cost.

The costs associated with development and purchasing, along with the detailed information of the system necessary to perform health and usage monitoring, have limited application to very expensive systems that are operated over long time spans. Applications of HUMS to vehicles have been primarily performed on fixed-wing aircraft ("Prognostics..." 2004, Trammel 1997, Hunt 2001) and rotorcraft (Ellerbrock 1999, Evans 2002, Bechhoefer 2004, Gordon 1991.) Other notable applications include an artillery system (Araiza 2002), manufacturing facility (Li 1995) and power plant (Jarrell 2006.) The life cycle cost and safety issues associated with these applications justify the development of complicated HUMS. The development and unit cost of a HUMS applied to a military land vehicle would need to be much less. The cost to develop a military ground vehicle system is often several orders of magnitude less than that of an aircraft, so expenditures for the development of a HUMS would have to be reduced by a relative proportion. In addition, cost of the HUMS could not be a significant portion of the vehicle cost. Redesign of components or replacement of the entire system may be a preferred alternative if the unit cost of a HUMS is prohibitive.

Some relatively low-cost HUMS have been developed for an elevator system (Yan 2005) and computer server applications (Schuster 2004). The specialized load cases and failure mechanisms in these examples limit the relevance to military ground vehicle platforms. A survey of HUMS technologies for electronics has been performed, but many of the techniques discussed provide health and usage information specific to a single device, board or component (Vichare 2006.) The additional cost for hardware and development may be difficult to justify for a military ground vehicle if insight is limited to a specific component, board or even device. One of the few instances of developing a HUMS for a ground vehicle was focused on the assessment of vibration for rotating components within the turbine engine of a M1 Abrams tank (Greitzer 2002.) This work involved monitoring the rotating components for indications of imminent failure. A model based on detecting precursors to failure requires detailed characterization of damage tolerant components and is not applicable or justifiable from a cost standpoint to many of the other components of a ground vehicle system. A generalized model is needed that could provide inputs into a large number of inexpensive components.

A HUMS applied to a military ground vehicle would also require sensors reliable enough that the HUMS would not contribute significantly to the total platform malfunctions. Rough terrain, extreme temperature fluctuations, dust and moisture are all commonly experienced on military ground vehicle systems and can be damaging to the sensors. Many of the sensors available for use in aircraft, plant, or electronic applications would not survive long in this field environment. Frequent need for replacement or calibration would counter the goals of increasing durability and readiness, while decreasing the logistics footprint of the platform. In order for these environmental hazards to be minimized, a limited set of robust sensors must be utilized for the HUMS.

Another key element for the application of a HUMS to a ground vehicle is that the system must be based on simple algorithms whose computation can be performed on-board the vehicle. Calculations on the type of data required for the accurate estimation of fatigue in addition to the error-checking algorithms and digitization requires significant computational capabilities, but the bandwidth required for raw data transfer if performed continuously or the storage of necessary of unprocessed data for long missions makes off-vehicle processing unfeasible. Algorithms for individual components must remain simple to allow multiple components to be monitored with inexpensive hardware.

The objective of this research was to develop a method for the creation and tuning of algorithms appropriate for a HUMS applied to a military land vehicle platform. The method developed was designed to be generic such that it could be applied to any mechanical component or electronic device, board or component that is primarily subjected to terrain induced loading. A baseline physics of failure analysis was performed on an example mechanical component and used to demonstrate that the proposed HUMS algorithms are appropriate and provide suitably accurate fatigue predictions (See Appendix A).

3.2 Demonstration Vehicle and Example Component

An eight wheeled Army vehicle was utilized as the demonstration vehicle for this research. Data were collected from candidate sensors for the HUMS. These included an accelerometer on the sprung mass of the vehicle, Global Positioning Satellite (GPS) data, J1708 data bus sensors, and trailing arm position via the built-in Height Management System (HMS) sensor. Strain data was also collected on a critical suspension component over multiple courses at the Yuma Proving Ground. A high-fidelity fatigue analysis was performed using commercially available software on the selected suspension component for each course. Results of the fatigue analysis were verified anecdotally based on failure rates. Further details regarding the example component have been intentionally obscured to minimize available information on failure modes of military equipment. It is the purpose of this work to present the method for application of remaining life prognostics algorithms and details of the exact component are unnecessary.

Figure 3.1: Army eight wheeled vehicle system

3.3 Terrain Identification

Many of the components on a military ground vehicle system are subjected primarily to terrain induced loading. Durability and fatigue testing is often performed based on an anticipated usage on primary, secondary and off-road test courses because the loading on many of the components change significantly for each terrain type. A HUMS that performed terrain identification could provide system level information on usage and fatigue estimates for multiple components with a very simple set of algorithms.

In order to develop and test a terrain identification procedure, available course data were separated into sets that could be used for training and testing algorithms. Each set included at minimum one test course described as primary, secondary, and off-road. Table 3.1 provides the results of the high fidelity fatigue analysis of measured strain data using the commercial fatigue analysis software package nSoft. A multi-axial crack initiation approach based on a strain gauge rosette was applied in conjunction with the Fatemi-Socie damage accumulation method (Fatemi 1988) to make damage predictions. Fatigue damage calculated for the entire course was divided by the number of twenty second intervals where average speed was above 1.61 kilometers per hour (1 mile per hour) that were necessary to traverse the course.

Table 3.1: Average fatigue damage per 20 seconds exposure

Terrain Type	**Training Data Set**	**Testing Data Set**
Primary	3.43E-06	1.00E-09
Secondary	7.80E-07	7.70E-08
Off-Road	3.61E-05	7.27E-06

3.3.1 Sample Statistics

In order to identify terrain, it was necessary to develop a simple method to determine terrain type from potential HUMS sensors. Trailing arm position via the HMS sensor and sprung mass acceleration were selected as candidates likely to be indicative of terrain type. Training data from potential HUMS sensors were sectioned into 20 second intervals and kurtosis, root mean square (RMS), standard deviation and skewness were plotted versus average speed calculated from the GPS sensor. Results from the HMS sensor and vertical accelerometer located on the sprung mass with average speed greater than 1.61 kilometers per hour (1 mile per hour) are shown in Figures 3.2 and 3.3 respectively.

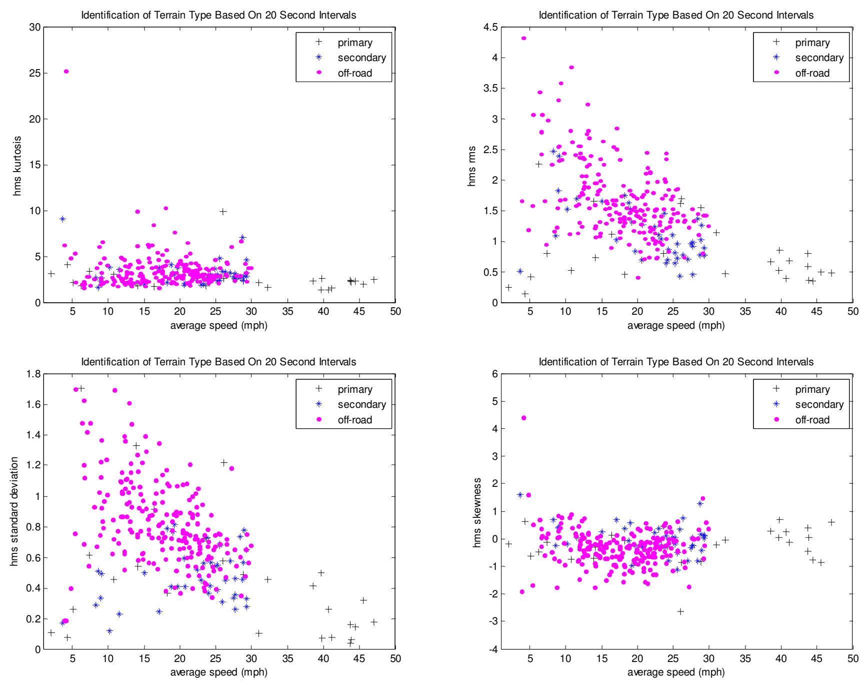

Figure 3.2: HMS statistics comparison versus average GPS speed

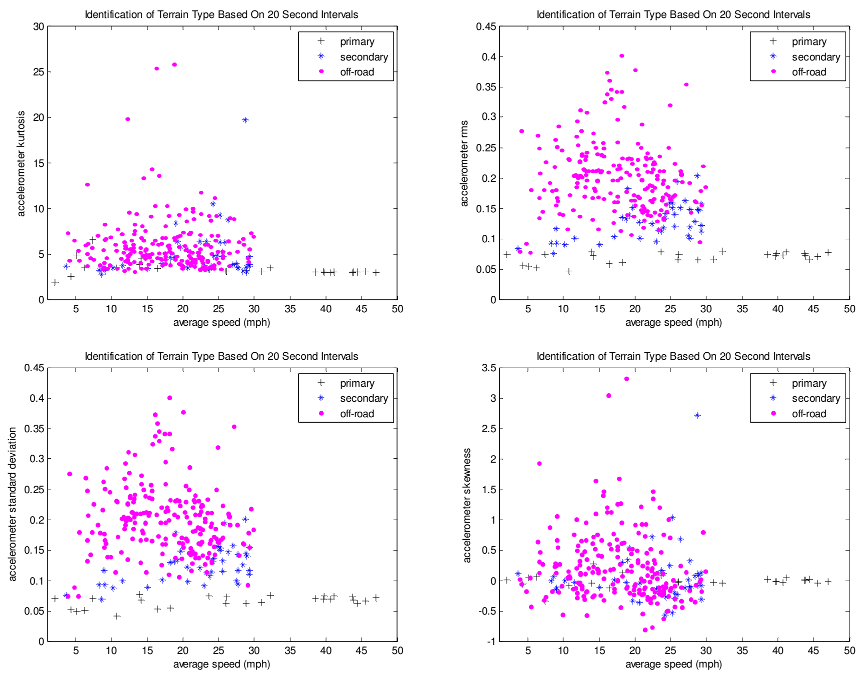

Figure 3.3: Accelerometer statistics comparison versus average GPS speed

Careful examination of Figures 3.2 and 3.3 show accelerometer RMS, standard deviation and kurtosis provide good differentiation of primary, secondary and off-road courses when plotted versus average speed. As would be expected of vertical accelerometer data based on terrain, the RMS and standard deviation values are nearly identical. This is due to the fact that when the mean is zero, the standard deviation and RMS statistics are identical. Gravitational acceleration was zeroed out of this data so the mean is very near zero for most samples. Skewness values for both sensors showed fairly random distribution of the data, and HMS sensor RMS, standard deviation and kurtosis showed less separation than accelerometer statistics. Accelerometer RMS, standard deviation and kurtosis were selected as candidate statistics for the terrain identification algorithms.

3.3.2 Evaluation Procedure

In order for the statistics to be compared numerically, it was necessary to develop a repeatable, automated process to divide the state-space into regions of primary, secondary and off-road terrains. In addition, this process would need to take into account the unequal number of tested data points in each category. The first step taken was to remove data points where the average speed was below 1.61 kilometers per hour (1 mile per hour) from the data set. It was assumed that points where the average speed was below 1.61 kilometers per hour (1 mile per hour) were indicative of times when the vehicle was mainly stationary and would not be subject to terrain induced loading. A least squares fit linear regression was performed on the remaining data in each category and the standard deviation of the residuals from the fit were calculated. Boundaries were set by determining the point between the two bordering regression lines where the number of residual standard deviations from each corresponding regression line was equal. The equation for the line through these points was found and used as the boundary between regions. Figures 3.4 and 3.5 illustrate this procedure.

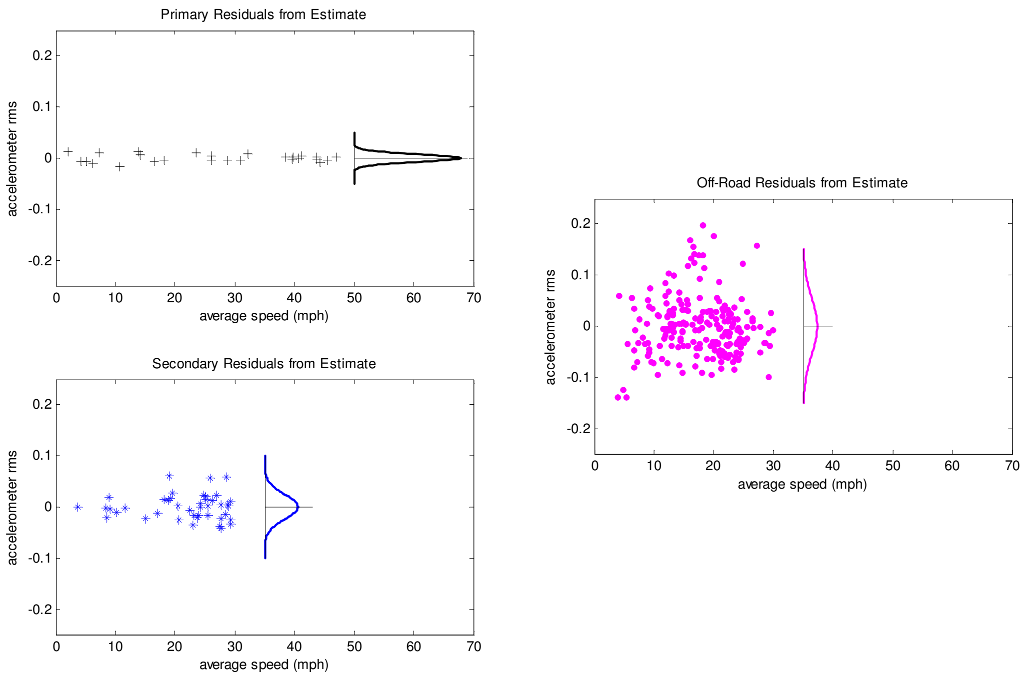

Figure 3.4: Calculating standard deviation of residuals from linear fit

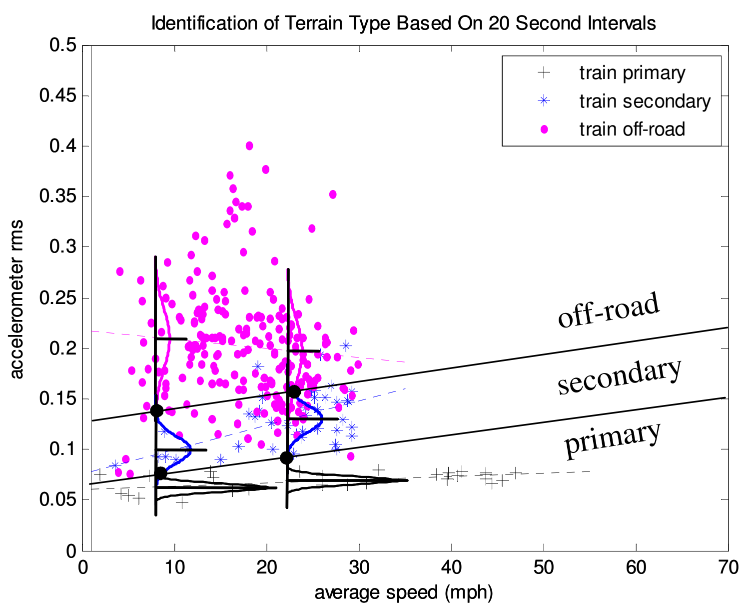

Figure 3.5: Automated procedure for defining terrain regions

Data that fell below the lines defining the terrain boundaries were considered primary terrain for this model. Data above the lines were defined as off-road terrain and the remaining data was considered secondary terrain. This ensured the regions were mutually exclusive within the reasonable state-space. Terrain boundaries did not overlap for the data studied here, but this may become an issue as the model is applied to other vehicles, sensors, or statistics.

Data from the training set were used to calculate terrain boundaries. Testing data were then used to objectively test the accuracy of the boundary. For reporting purposes, terrain identification accuracy was calculated as the average of the ratio of intervals correctly identified in each category to the number of intervals measured in each category.

3.3.3 Sample Window Size

One of the critical parameters deemed worthy of investigation for this model was the length of time used for each data point. Speed was observed to change significantly over sections longer than 20 seconds for many of the courses used in this analysis. Average speed was thought to be misleading for longer time segments, so 20 seconds was selected as the upper limit for sample windows investigated. A lower limit was set at 0.5 seconds. A sample window shorter than 0.5 seconds was expected to contain too little terrain information to provide good statistical measures. An initial inspection performed visually of different sample window sizes did not show obvious superiority of one sample rate. Thus, the automated procedure was used to evaluate the accuracy of terrain identification for sample window sizes ranging from 0.5 to 20 seconds.

3.4 Fatigue Estimation

In order to evaluate accuracy of fatigue damage estimations, a representative usage made up of the available terrain types was necessary to compare the variables equitably. Requirements documents indicate a predicted usage in terms of primary, secondary and off-road courses for each variant of the demonstration vehicle. Durability tests for army combat vehicles are commonly 32,200 kilometers (20,000 miles) in length following and were assumed to follow the expected terrain profile for the most common variant. High fidelity fatigue damage estimates based on measured strain data for each of the courses were scaled based on Miner's damage summation rule (Miner 1945) which relates number of cycles n_k, and number of cycles to failure N_k to damage D.

$$\sum_{k=1}^{m} \frac{n_k}{N_k} = D \tag{1}$$

High fidelity fatigue damage predictions were made for the training and testing data sets undergoing a 32,200 kilometer (20,000) mile durability test.

A model similar to Miner's damage summation rule was developed for predicting fatigue damage from terrain exposure. This model relates the number of samples of exposure to one of the three terrain types s_k and the predicted number of samples to failure S_k to damage D.

$$\sum_{k=1}^{3} \frac{s_k}{S_k} = D \qquad (2)$$

The inverse of the predicted number of cycles to failure is the expected damage per sample. Expected damage per sample is the average fatigue damage per exposure window from the training data set. Values for 20 second segments are shown in Table 3.1. Segments that fell in the primary, secondary, and off-road terrain regions were scaled using Miner's damage summation rule to fit the durability profile and an estimated damage D was calculated and compared to the high fidelity fatigue model for the testing data sets. Accuracy of the fatigue damage estimation was calculated as the ratio of damage predicted using the terrain identification model scaled to a 32,200 kilometer (20,000) mile durability test to the damage predicted from the high fidelity fatigue model scaled to a 32,200 kilometer (20,000) mile durability test.

3.5 Results

Terrain identification and fatigue estimates were made based on accelerometer RMS, standard deviation and kurtosis for various sample window sizes. Training data sets were used to develop terrain identification regions and independent data sets were used for testing purposes. Results from the test data sets are plotted in Figures 3.6 and 3.7. Terrain identification accuracy generally increased with longer sample window sizes. Accelerometer RMS was shown to be most accurate at terrain identification, with all values between 32% and 81% accurate. Fatigue damage estimates were less accurate. Accuracy varied between 239% and 540% of that predicted by the high fidelity fatigue model.

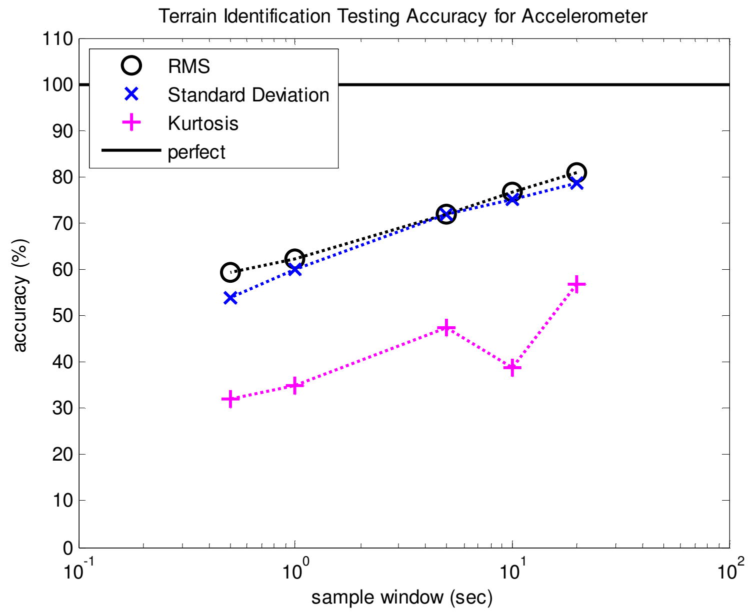

Figure 3.6. Terrain identification accuracy for various statistics

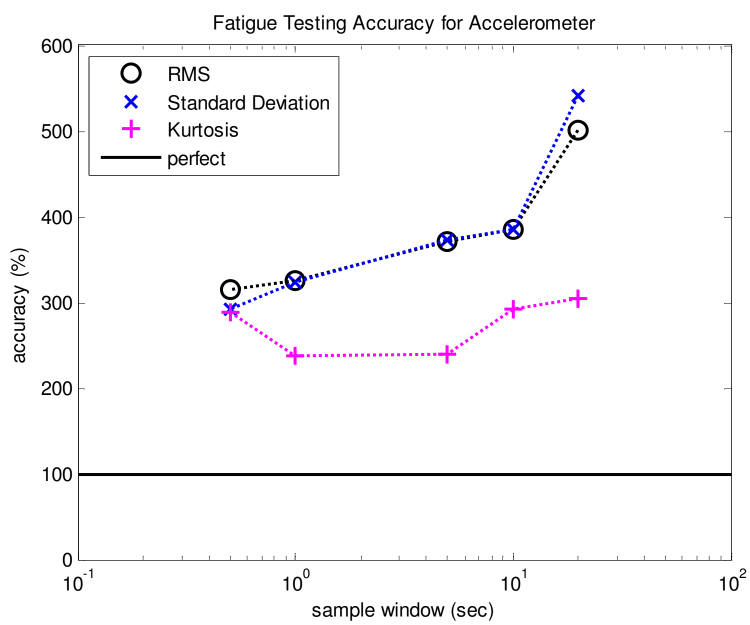

Figure 3.7. Fatigue estimate accuracy for various statistics

One of the major assumptions made in the fatigue damage estimation model proposed in Equation (2) is that the average fatigue damage is reasonably consistent between the training and testing data sets for the terrain types. As can be seen in Table 3.1, this assumption was not entirely accurate. Thus the primary reason that the fatigue damage estimates were more damaging than predicted by the high fidelity fatigue estimation was that the off-road terrain used in training the model is considerably more damaging than that of testing. In order to make a prediction with accuracy commensurate with the terrain identification accuracy, fatigue damage of training data needs to be very similar to the data used in testing. Typically, several courses are used during a durability test to represent each of the terrain types. Using multiple courses in the fatigue damage estimates would minimize course specific events and result in a more accurate fatigue prediction. The number of samples until failure for each terrain could be adjusted as additional test data is collected or as failures occur during fielded usage.

3.6 *Conclusions*

A simple model was developed that identifies terrain exposure from robust sensors located at a benign location within a vehicle system. Terrain exposure was then used to estimate fatigue damage accumulated on a particular component with reasonable success. A model such as the one described here that estimates fatigue damage based on terrain exposure is an ideal candidate for use in HUMS applied to military ground vehicles. Terrain induced loading is the primary failure mechanism for many of the electronic and mechanical components within a military ground vehicle system. A single set of sensors and algorithms can provide terrain exposure for an entire vehicle. Estimating fatigue damage accumulated on individual components is merely a matter of determining scale factors associated with each terrain type. Thus a large number of components can be monitored with a small set of robust sensors in benign locations. Computational power and data processing can be performed by reasonably priced on-board electronics. This permits condition based maintenance to be performed based on the estimated health of the individual components, raising the reliability and availability of monitored vehicles. In addition, as terrain exposure data is collected and archived, higher fidelity estimates of vehicle usage can be utilized to improve the design of future military vehicle systems.

While the accuracy of the model developed could be improved, results are within the typical error of fatigue estimates for similar components subjected to widely varying vibration inputs. Selection of representative terrain was shown to be critical for accurately training fatigue models. Knowledge of damage rates for each terrain type or a high fidelity fatigue model applied to representative test data are essential for accurate fatigue predictions. Further refinement of terrain type and road conditions tested may provide improved accuracy of terrain identification model. More complicated models and sensor suites may be necessary for components that are susceptible to multiple sources of load such as thermal and vibration.

Chapter 4: Terrain Identification for Mechanical Components

In order to apply a HUMS to mechanical components on a military ground vehicle, simplified algorithms that drive terrain exposure from a basic set of sensors and estimate fatigue damage accumulated on components whose loading comes primarily from terrain have been developed. Inputs and statistical parameters are evaluated for this model based on accuracy of terrain identification and quality of fatigue prediction on an example component. The remainder of material in Chapter 4 is presented as it was formatted for submission to the Journal of the Institute of Environmental Sciences and Technology and contains repeated background information. To avoid repeated information, readers should skip to section 4.2.

4.1 Background

Reliability of military vehicle systems is being driven upward to mitigate life cycle cost and improve operational availability and readiness. New requirements for functionality and performance are resulting in increasingly complex vehicle systems. In order to address these conflicting issues, novel ways to improve reliability and readiness are needed. One method that is favored in the Department of Defense is the inclusion of a Health and Usage Monitoring System or HUMS within a vehicle platform. HUMS can be practically defined as a system of sensors, processors and algorithms that give an indication of remaining component life. These systems provide an indication of the usage of an individual vehicle and the effect of the environmental factors on specific monitored components. The resulting data is processed and provides information to operators, maintainers, and mission planning personnel as to which components should be serviced, which vehicles have the lowest probability of failure during a mission, and what the past usage of the vehicle has been. With good management, this information can be used to increase availability and reliability, while decreasing overall maintenance and system cost.

The costs associated with development and purchasing, along with the detailed information of the system necessary to perform health and usage monitoring, have limited application to very expensive systems that are operated over long time spans. Applications of HUMS to vehicles have been primarily performed on fixed-wing aircraft (Anon 2004, Trammel 1997, Hunt 2001) and rotorcraft (Ellerbrock 1999, Evans 2002, Bechhoefer 2004, Gordon 1991.) Other notable applications include an artillery system (Araiza 2002), manufacturing facility (Li 1995) and power plant (Jarrell 2006.) The life cycle cost and safety issues associated with these applications justify the development of complicated HUMS. The development and unit cost of a HUMS applied to a military land vehicle would need to be much less. The cost to develop a military ground vehicle system is often several orders of magnitude less than that of an aircraft, so expenditures for the development of a HUMS would have to be reduced by a relative proportion. In addition, cost of the HUMS could not be a significant portion of the vehicle cost. Redesign of components or replacement of the entire system may be a preferred alternative if the unit cost of a HUMS is prohibitive.

Some relatively low-cost HUMS have been developed for an elevator system (Yan 2005) and computer server applications (Schuster 2004). The specialized load cases and failure mechanisms in these examples limit the relevance to military ground vehicle platforms. A survey of HUMS technologies for electronics has been performed, but many of the techniques discussed provide health and usage information specific to a single device, board or component (Vichare 2006.) The additional cost for hardware and development may be difficult to justify for a military ground vehicle if insight is limited to a specific component, board or even device. One of the few instances of developing a HUMS for a ground vehicle was focused on the assessment of vibration for rotating components within the turbine engine of a M1 Abrams tank (Greitzer 2002.) This work involved monitoring the rotating components for indications of imminent failure. A model based on detecting precursors to failure requires detailed characterization of damage tolerant components and is not applicable or justifiable from a cost standpoint to many of the other components of a ground vehicle system. A generalized model is needed that could provide inputs into a large number of inexpensive components.

A HUMS applied to a military ground vehicle would also require sensors reliable enough that the HUMS would not contribute significantly to the total platform malfunctions. Rough terrain, extreme temperature fluctuations, dust and moisture are all commonly experienced on military ground vehicle systems and can be damaging to the sensors. Many of the sensors available for use in aircraft, plant, or electronic applications would not survive long in this field environment. Frequent need for replacement or calibration would counter the goal of increasing durability and readiness, while decreasing the logistics footprint of the platform. In order for these environmental hazards to be minimized, a limited set of robust sensors must be utilized for the HUMS.

Another key element for the application of a HUMS to a ground vehicle is that the system must be based on simple algorithms whose computation can be performed on-board the vehicle. Calculations on the type of data required for the accurate estimation of fatigue in addition to the error-checking algorithms and digitization requires significant on-board computational capabilities, but the bandwidth required for continuous raw data transfer or the unprocessed data storage of long missions makes off-vehicle processing unfeasible. Algorithms for individual components must remain simple to allow multiple components to be monitored with inexpensive hardware.

The objective of this research was to develop a method for the creation and tuning of algorithms appropriate for a HUMS applied to a military land vehicle platform. The method developed was designed to be generic such that it could be applied to any mechanical component subjected primarily to terrain induced loading. A baseline physics of failure analysis was performed on an example component and used to demonstrate that the proposed HUMS algorithms are appropriate and provide suitably accurate fatigue predictions (See Appendix A).

4.2 Demonstration Vehicle and Example Component

An eight wheeled Army vehicle similar to the one shown in Figure 4.1 was utilized as the demonstration vehicle for this research. Data were collected from candidate sensors for the HUMS. These included an accelerometer on the sprung mass of the vehicle, Global Positioning Satellite (GPS) data, and J1708 data bus sensors. Strain data was also collected near a welded connection on a critical steering component over multiple courses at the Yuma Proving Ground. A high-fidelity fatigue analysis was performed on the strain data for each course using the commercially available software.

Figure 4.1: Army eight wheeled vehicle system

Figure 4.2 shows an example component with its welded joint. A physics of failure analysis was performed to determine the fatigue life for the component (See Appendix A). Root cause of failure was determined to be caused, in part, by terrain specific loading. The steering components are also subjected to other forces such as turning loads, but fatigue damage to this component was traced to the terrain induced loading. Further details regarding the example component have been intentionally obscured to minimize available information on failure modes of military equipment. It is the purpose of this work to present the method for application of remaining life prognostics algorithms and details of the exact component are unnecessary.

Figure 4.2: Example component with fatigue crack

4.3 Terrain Identification

Many of the components on a military ground vehicle system are subjected primarily to terrain induced loading. Durability and fatigue testing is often performed based on an anticipated usage on primary, secondary and off-road test courses because the loading on many of the components change significantly for each terrain type. A HUMS that performed terrain identification could provide system level information on usage and fatigue estimates for multiple components with a very simple set of algorithms.

In order to develop and test a terrain identification procedure, available course data were separated into sets that could be used for training and testing algorithms. Each set included at minimum one test course described as primary, secondary, and off-road.

A range/mean histogram was made for each course based on strain data collected on a healthy component from a rosette located near the weld toe. Observed crack initiation sites and finite element analysis were used to locate the critical area for fatigue. Fatigue damage accumulated and life predictions were then made for each course using the British Weld Standard BS 7608 (1993.) Life predictions were verified anecdotally based on failures and usage rates of fielded systems. Table 4.1 provides the results of the high fidelity fatigue analysis of measured strain data. Fatigue damage calculated for the entire course was divided by the number of twenty second intervals where average speed was above 1.61 kilometers per hour (1 mile per hour) that were necessary to traverse the courses in each category.

Table 4.1: Average fatigue damage per 20 seconds exposure

Terrain Type	Training Data Set	Testing Data Set
Primary	6.25E-07	2.82E-07
Secondary	1.35E-04	6.10E-06
Off-Road	2.30E-04	2.70E-05

4.3.1 Sample Statistics

In order to identify terrain, it was necessary to develop a simple method to determine terrain type from potential HUMS sensors. A sprung mass accelerometer was selected as a candidate likely to be indicative of terrain type. Training data from the potential HUMS sensor was sectioned into 20 second intervals and kurtosis, root mean square (RMS), standard deviation and skewness were plotted versus average speed calculated from the GPS sensor. Results from the vertical accelerometer located on the sprung mass with average speed greater than 1.61 kilometers per hour (1 mile per hour) are shown in Figure 4.3.

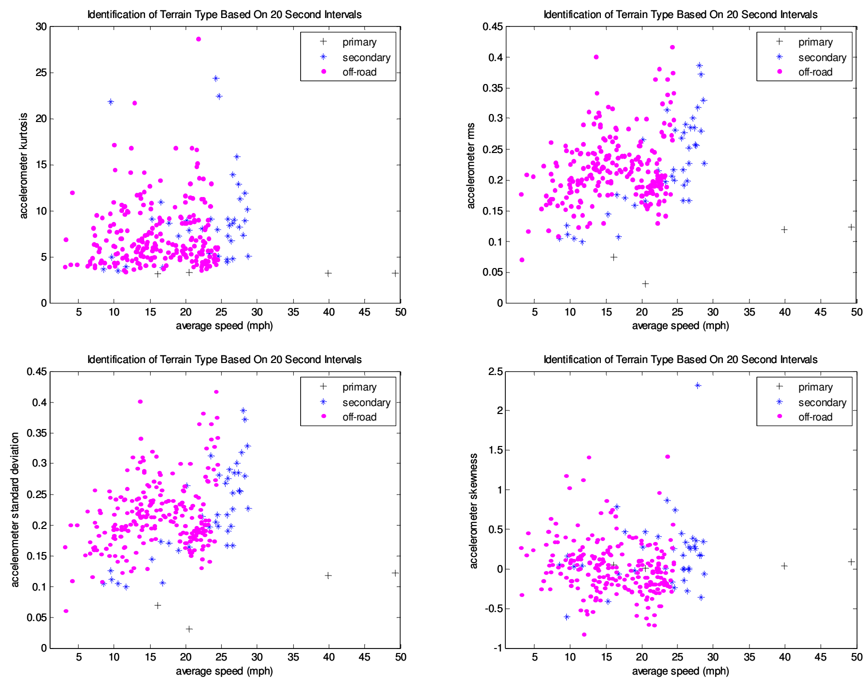

Figure 4.3: Accelerometer statistics comparison versus average GPS speed

Careful examination of Figure 4.3 shows accelerometer RMS, standard deviation and kurtosis provide differentiation of primary, secondary and off-road courses when plotted versus average speed. As would be expected of vertical accelerometer data based on terrain, the RMS and standard deviation values are nearly identical. This is due to the fact that when the mean is zero, the standard deviation and RMS statistics are identical. Gravitational acceleration was zeroed out of this data so the mean is very near zero for most samples. Skewness values showed fairly random distribution of the data. Accelerometer RMS, standard deviation and kurtosis were selected as potential candidate statistics for the terrain identification algorithms.

4.3.2 Evaluation Procedure

In order for the statistics to be compared numerically, it was necessary to develop a repeatable, automated process to divide the state-space into regions of primary, secondary and off-road terrains. In addition, this process would need to take into account the unequal number of tested data points in each category. The first step taken was to remove data points where the average speed was below 1.61 kilometers per hour (1 mile per hour) from the data set. It was assumed that points where the average speed was below 1.61 kilometers per hour (1 mile per hour) were indicative of times when the vehicle was mainly stationary and not subject to terrain induced loading. A least squares fit linear regression was performed on the remaining data in each category and the standard deviation of the residuals from the fit were calculated. Boundaries were set by determining the point between the two bordering regression lines where the number of residual standard deviations from each corresponding regression line was equal. The equation for the line through these points was found and used as the boundary between regions. Figures 4.4 and 4.5 illustrate this procedure.

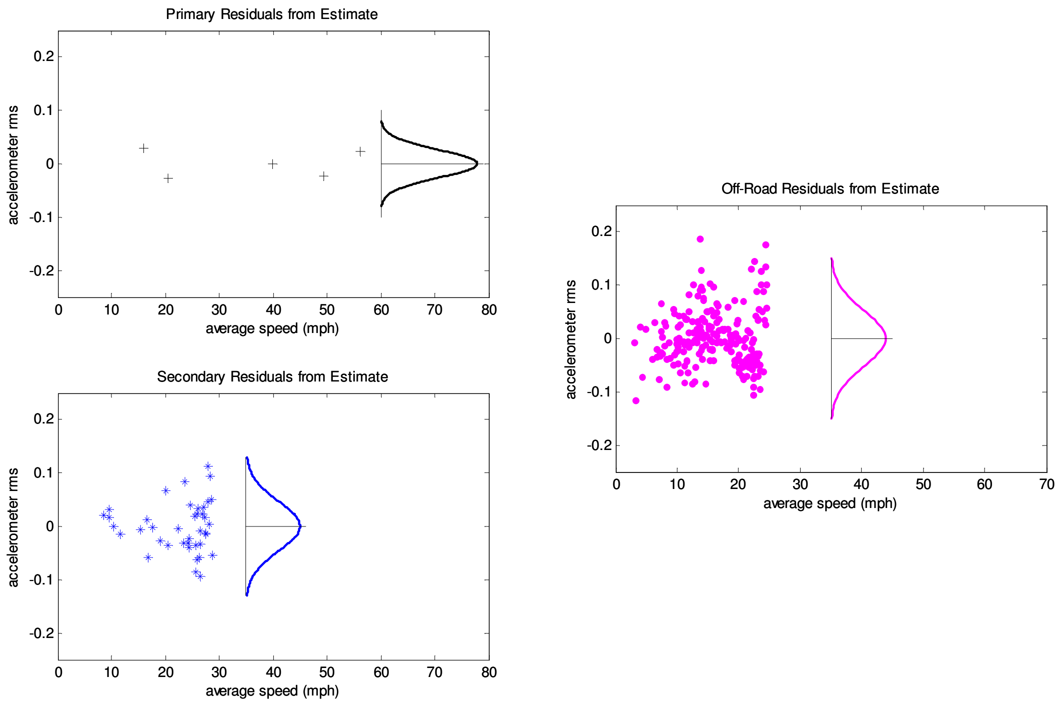

Figure 4.4: Calculating standard deviation of residuals from linear fit

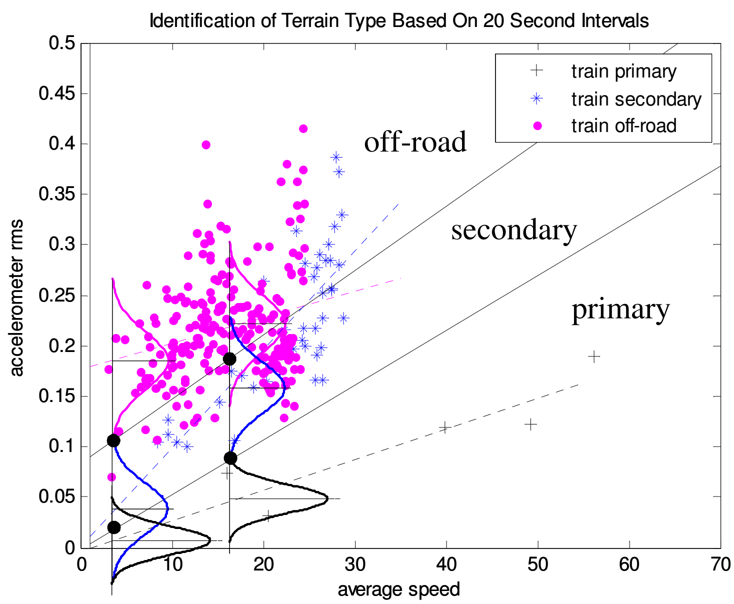

Figure 4.5: Automated procedure for defining terrain regions

Data that fell below the lines defining the terrain boundaries were considered primary terrain for this model. Data above the lines were defined as off-road terrain and the remaining data were considered secondary terrain. This ensured the regions were mutually exclusive within the reasonable state-space. Terrain boundaries did not overlap for the data studied here, but this may become an issue as the model is applied to other vehicles, sensors, or statistics.

Data from the training set were used to calculate terrain boundaries. Testing data were then used to objectively test the accuracy of the boundary. For reporting purposes, terrain identification accuracy was calculated as the average of the ratio of intervals correctly identified in each category to the number of intervals measured in each category.

4.3.3 Sample Window Size

One of the critical parameters deemed worthy of investigation for this model was the length of time used for each data point. Speed was observed to change significantly over sections longer than 20 seconds for many of the courses used in this analysis. Average speed was thought to be misleading for longer time segments, so 20 seconds was selected as the upper limit for sample windows investigated. A lower limit was set at 0.5 seconds. A sample window shorter than 0.5 seconds was expected to contain too little terrain information to provide good statistical measures. An initial inspection performed visually of different sample window sizes did not show obvious superiority of one sample size. Thus, the automated procedure was used to evaluate the accuracy of terrain identification for sample window sizes ranging from 0.5 to 20 seconds.

4.4 Fatigue Estimation

In order to evaluate accuracy of fatigue damage estimations, a representative usage made up of the available terrain types was necessary to compare the variables equitably. Requirements documents indicate a predicted usage in terms of primary, secondary and off-road courses for each variant of the demonstration vehicle. Durability tests for army combat vehicles are commonly 32,200 kilometers (20,000 miles) in length and are assumed to follow the expected terrain profile for the most common variant. High fidelity fatigue damage estimates based on measured strain data for each of the courses were scaled based on Miner's damage summation rule (Miner 1945) which relates number of cycles n_k, and number of cycles to failure N_k to damage D.

$$\sum_{k=1}^{m} \frac{n_k}{N_k} = D \qquad (1)$$

High fidelity fatigue damage predictions were made for the training and testing data sets undergoing a 32,200 kilometer (20,000) mile durability test.

A model similar to Miner's damage summation rule was developed for predicting fatigue damage from terrain exposure. This model relates the number of samples of exposure to one of the three terrain types s_k and the predicted number of samples to failure S_k to damage D.

$$\sum_{k=1}^{3} \frac{s_k}{S_k} = D \qquad (2)$$

The inverse of the predicted number of cycles to failure is the expected damage per sample. Expected damage per sample is the average fatigue damage per exposure window from the training data set. Values for 20 second segments are shown in Table 4.1. Segments that fell in the primary, secondary, and off-road terrain regions were scaled using Miner's damage summation rule to fit the durability profile and an estimated damage D was calculated and compared to the high fidelity fatigue model for the testing data sets. Accuracy of the fatigue damage estimation was calculated as the ratio of damage predicted using the terrain identification model scaled to a 32,200 kilometer (20,000 mile) durability test to the damage predicted from the high fidelity fatigue model scaled to a 32,200 kilometer (20,000 mile) durability test.

4.5 Results

Terrain identification and fatigue estimates were made based on accelerometer RMS, standard deviation and kurtosis for various sample window sizes. Training data sets were used to develop terrain identification regions and independent data sets were used for testing purposes. Results from the test data sets are plotted in Figures 4.6 and 4.7. Terrain identification accuracy based on RMS and standard deviation generally increased with longer sample window sizes. Kurtosis showed no clear trend based on sample window size. Accelerometer standard deviation was shown to be most accurate at terrain identification, with all values between 46% and 55% accurate. Fatigue damage estimates were less accurate. Accuracy from accelerometer standard deviation varied between 450% and 682% of that predicted by the high fidelity fatigue model.

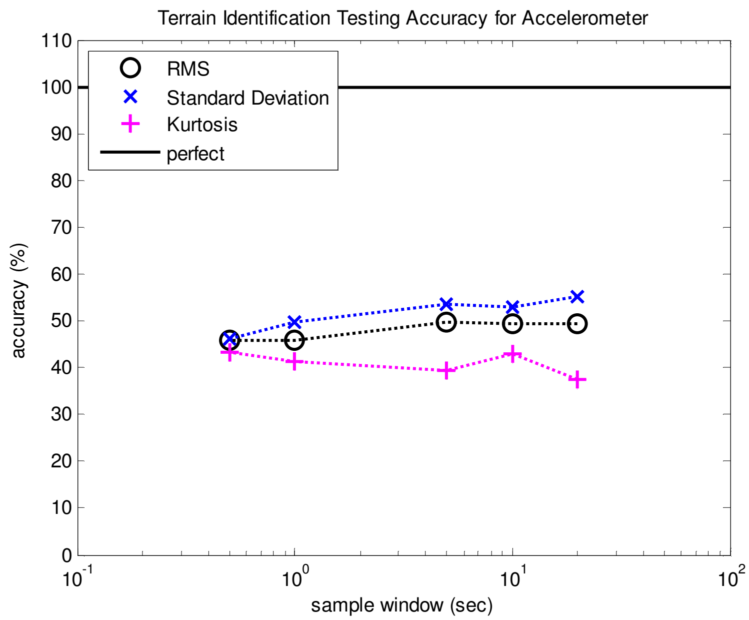

Figure 4.6. Terrain identification accuracy for various statistics

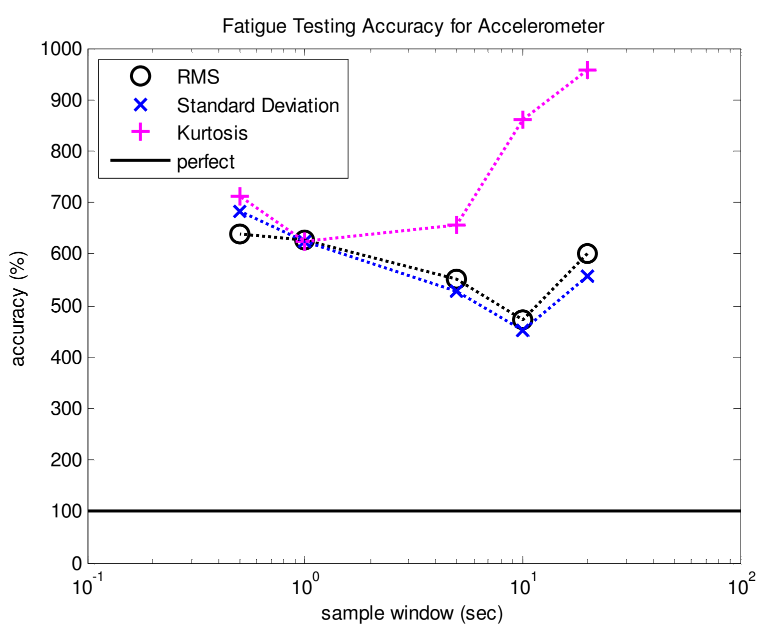

Figure 4.7. Fatigue estimate accuracy for various statistics

In order for the fatigue damage estimation model proposed in Equation (2) to provide accurate projections, it is necessary that the average fatigue damage is reasonably consistent between the training and testing data sets for the terrain types. As can be seen in Table 4.1, this assumption was not entirely accurate. Primary and off road terrain provided relatively good matches, but secondary varied significantly between the training and testing data sets. Thus the main reason that the fatigue damage estimates were more damaging than predicted by the high fidelity fatigue estimation was that the secondary terrain used in training the model is considerably more damaging than that of testing. In order to make a prediction with accuracy commensurate with the terrain identification accuracy, fatigue damage of training data needs to be very similar to the data used in testing. Typically, several courses are used during a durability test to represent each of the terrain types. Using multiple courses in the fatigue damage estimates would minimize course specific events and result in a more accurate fatigue prediction. The number of samples until failure for each terrain could be adjusted as additional test data is collected or as failures occur during fielded usage.

4.6 Conclusions

A simple model was developed that identifies terrain exposure from robust sensors located at a benign location within a vehicle system. Terrain exposure was then used to estimate fatigue damage accumulated on a particular component with reasonable success. A model such as the one described here that estimates fatigue damage based on terrain exposure is an ideal candidate for use in HUMS applied to military ground vehicles. Terrain induced loading is the primary failure mechanism for many of the electronic and mechanical components within a military ground vehicle system. A single set of sensors and algorithms can provide terrain exposure for an entire vehicle. Estimating fatigue damage accumulated on individual components is merely a matter of determining scale factors associated with each terrain type. Thus a large number of components can be monitored with a small set of robust sensors in benign locations. Computational power and data processing can be performed by reasonably priced on-board electronics. This permits condition based maintenance to be performed based on the estimated health of the individual components, raising the reliability and availability of monitored vehicles. In addition, as terrain exposure data is collected and archived, higher fidelity estimates of vehicle usage can be utilized to improve the design of future military vehicle systems.

While the accuracy of the model developed could be improved, results are within the typical error of fatigue estimates for similar components subjected to widely varying vibration inputs. Selection of representative terrain was shown to be critical for accurately training fatigue models. Knowledge of damage rates for each terrain type or a high fidelity fatigue model applied to representative test data are essential for accurate fatigue predictions. Further refinement of terrain type and road conditions tested may provide improved accuracy of terrain identification model. More complicated models and sensor suites may be necessary for components that are susceptible to multiple sources of load.

Chapter 5: Acceleration-Based Strain Estimation

This chapter defines a set of more computationally complex algorithms that use measured acceleration to predict strain and fatigue damage that is suitable for special load cases where acceleration waveforms can be shown to be similar to strain. The feasibility of using vibratory inputs from an accelerometer to make component fatigue predictions for a military wheeled vehicle system is explored and the use of limited subsets of data for algorithm training are evaluated. An example component is used to demonstrate that the proposed HUMS algorithms are appropriate and provide suitably accurate fatigue predictions. The remainder of material in Chapter 5 is presented as it was formatted for submission to the Journal of the Institute of Environmental Sciences and Technology and contains repeated background information. To avoid repeated information, readers should skip to the last two paragraphs in section 5.1.

5.1 Background

Reliability, availability and maintainability (RAM) are critical requirements for military ground vehicle programs. These requirements help to ensure that a system meets user needs in a timely manner and at a reasonable price. The increasing complexity of military vehicle systems coupled with the user's desire for expanded performance is reducing design margins and making RAM requirements more difficult to achieve. Innovative technologies need to be developed and applied to maintain high performance materiel at reasonable prices. One method that is being promoted in the Department of Defense is the inclusion of a Health and Usage

Monitoring System or HUMS within a vehicle platform. HUMS can be practically defined as a system of sensors, processors and algorithms that give an indication of remaining component life. These systems provide an indication of the usage of individual vehicles and the effect of the environmental factors on specific monitored components. The resulting data are processed and provide information to operators, maintainers, and mission planning personnel as to which components should be serviced, which vehicles have the lowest probability of failure during a mission, and what the past usage of the vehicle has been. With good management, this information can be used to increase availability and reliability, while decreasing overall maintenance and system cost.

The costs associated with development and purchasing, along with the detailed information of the system necessary to perform health and usage monitoring, typically limit application to critical components within expensive systems that are subjected to relatively simple environmental and loading conditions and operated over long time spans. Applications of HUMS to vehicles have been primarily performed on fixed-wing aircraft ("Prognostics..." 2004, Trammel 1997, Hunt 2001) and rotorcraft (Ellerbrock 1999, Evans 2002, Bechhoefer 2004, Gordon 1991.) Other notable examples include a HUMS developed for an artillery system (Araiza 2002), manufacturing facility (Li 1995) and power plant (Jarrell 2006.) The relevancy of the techniques and processes developed for these applications to a military ground vehicle is limited. These examples are exposed to environment and loading conditions that have significantly less variation than those of a ground vehicle. In order to address all the relevant load cases on a ground vehicle system, robust engineering models are needed to calculate damage accumulated. Use of these techniques on a military ground vehicle is also a challenge due to the fact that the life cycle cost associated with previous applications justify the development of complicated HUMS. The development and unit cost of a HUMS applied to a military land vehicle would need to be much less. The cost to develop a military ground vehicle system is often several orders of magnitude less than that of an aircraft, so expenditures for the development of a HUMS would have to be reduced by a relative proportion. In addition, cost of the HUMS could not be a significant portion of the vehicle cost. Redesign of components or replacement of the entire system may be a preferred alternative if the unit cost of a HUMS is prohibitive.

One previous instance of a HUMS applied to a ground vehicle focused on the damage caused by vibration of rotating components within the turbine engine of an M1 Abrams tank (Greitzer 2002.) Techniques developed for aircraft could be directly applied to this work which involved monitoring rotating components for indications of imminent failure, but detailed characterization of damage tolerant components is necessary to detect precursors to failure. The testing or analytical burden required to identify precursors to failure and the limitation of the information provided to a single failure mode within a single subsystem makes such applications hard to justify from a cost standpoint for even the most expensive ground vehicles.

There have been instances where a HUMS was developed for relatively low-cost applications such as an elevator system (Yan 2005) and computer servers (Schuster 2004.) A survey of HUMS technologies for electronics has been performed, and many of the techniques discussed provide health and usage information specific to a single device, board or component (Vichare 2006.) The specialized load cases and failure mechanisms in these examples limit the relevance to items on military ground vehicle platforms beyond electronics, however these examples are successful in demonstrating the practicality of applying a HUMS for specific components in a low-cost application.

A general set of algorithms for application of HUMS to a military ground vehicle system was developed based on the relationship of fatigue damage to terrain type (see Chapter 4.) Durability and fatigue testing are often performed based on an anticipated usage on primary, secondary and off-road terrains because the loading on many of the components changes significantly for each terrain type. These algorithms take advantage of the similarity of damage rates within each terrain type to estimate fatigue damage accumulated on individual components. One of the major advantages of this system is that a very simple set of sensors and algorithms provide damage estimates for multiple components. This effectively spreads the developmental and unit cost of the HUMS across many components. Accuracy of fatigue damage predicted from terrain identification algorithms varied by a factor of 4.5 and 6.8 to damage predicted by a high fidelity fatigue model. These results are within the typical error of fatigue estimates for similar components subjected to widely varying vibration inputs, but accuracy was shown to be highly dependent on identifying a fatigue damage per exposure time scale factor that is representative for all conditions within a terrain type. This requires significant testing on multiple courses that would represent the full range of scenarios that a military vehicle would encounter. The desire for a more accurate fatigue estimate and the ability to minimize algorithm training data required may justify more complex algorithms for some components. A model that could work in concert with terrain identification model to provide enhanced fatigue damage predictions while minimizing algorithm training data, would be useful for components deemed critical or safety related.

One of the major difficulties in application of a HUMS is the limitation caused by sensors. Any sensors used need to be reliable enough that the HUMS would not contribute significantly to the total platform malfunctions. Rough terrain, extreme temperature changes, dust and large fluctuations in humidity are all commonly experienced on military vehicle systems and can be damaging to a HUMS. Sensors are especially sensitive to these effects. Constant replacement or calibration requiring human interaction would be counter to the goals of increasing durability and readiness, while decreasing the logistics footprint of the platform. Strain measurements are desirable as an input to fatigue damage estimation models. However, the common method of measuring strain with adhesively bonded strain gauges is fraught with difficulties. Strain gauges are sensitive to temperature variations, and bonding can be an issue if expected to last the life of the component. Accelerometers are another common sensor which gives an indication of terrain induced loading. Accelerometers are relatively durable and reasonable in cost which makes them an ideal candidate for use in a HUMS applied to a military ground vehicle system.

The objectives of this research are to investigate the feasibility of using vibratory inputs from an accelerometer to make component fatigue predictions for a military wheeled vehicle system and examine methods to improve HUMS predictions for specific components. Use of limited subsets of data for algorithm training will also be evaluated. A baseline physics of failure analysis was performed on an example component and used to demonstrate that the proposed HUMS algorithms are appropriate and provide suitably accurate fatigue predictions (See Appendix A).

5.2 Demonstration Vehicle and Component

The hydraulic reservoir shown in Figure 5.1 was selected as a demonstration component for this study. This reservoir supplies fluid for a number of hydraulic subsystems within a wheeled army vehicle system. Fatigue cracking was noted during automotive testing and the root cause of failure was determined to be terrain induced vibration.

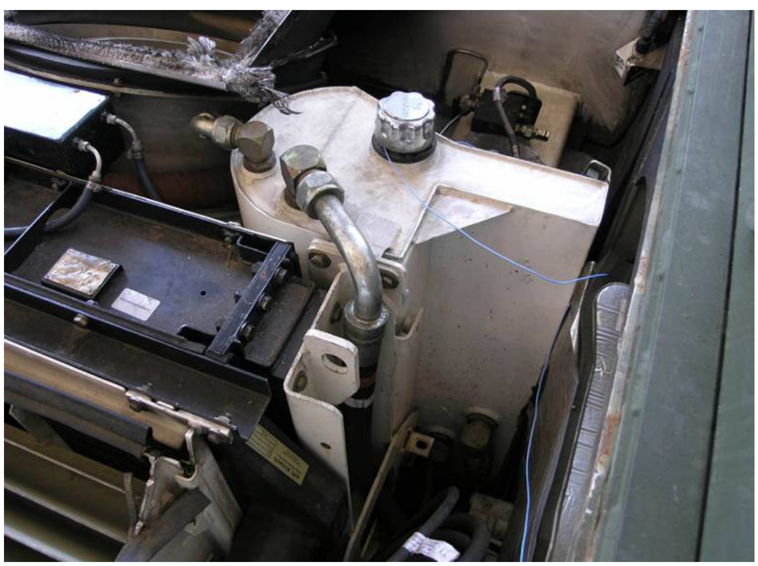

Figure 5.1: Hydraulic reservoir in Army wheeled vehicle

Instrumented data were taken from a series of test courses and obstacles determined to be damaging to the hydraulic reservoir at an Army facility. These included obstacles made up of 8, 10, 12 and 16 inch half rounds affixed to a flat road course, a series of gravel courses with periodic bumps to give defined root mean square values, and two severe off-road courses. Acceleration data were collected from several locations on the vehicle and reservoir, and strain data were collected for major failure locations. A high fidelity fatigue analysis was performed on the strain data for each course using commercially available software and stress life curves for weldments defined in the European Recommendations of Aluminum Alloy Structures Fatigue Design (1992.) Physical validation using shaker table testing based on measured acceleration showed failures closely matched high fidelity fatigue estimates. Further details regarding the example component have been intentionally obscured to minimize available information on failure modes of military equipment. It is the purpose of this work to present the method for application of remaining life prognostics algorithms and details of the exact component are unnecessary.

5.3 Waveform Comparison

Calculation of the principal angle during the fatigue analysis of the reservoir showed that strain in the most critical location was uniaxial along a single rosette leg. Vertical acceleration induced by terrain was determined to be the principal cause of failure, so a vertical accelerometer connected to the hull of the demonstration vehicle was selected for comparison with the critical strain. Figure 5.2 shows samples of the measured data for each of the course types.

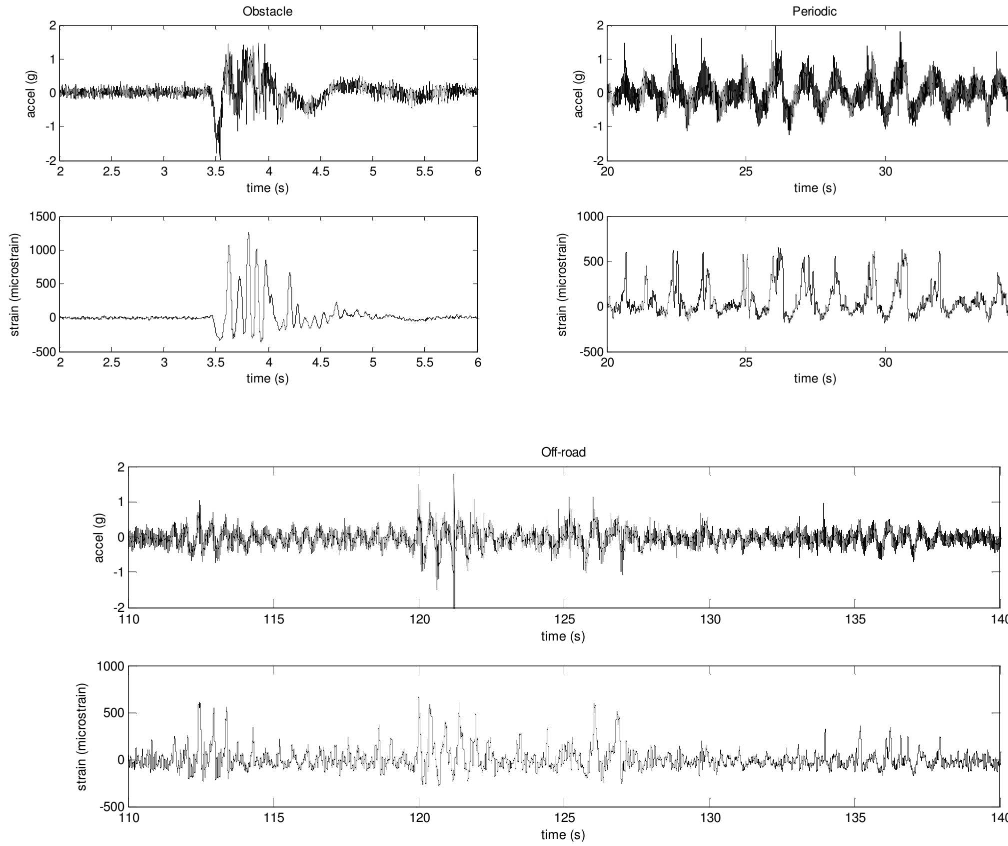

Figure 5.2: Sample strain and acceleration comparisons

As can be seen in Figure 5.2, the overall shape was very similar for the strain and acceleration measurements. Acceleration measurements appear to have significantly more high frequency, low amplitude cycles, and acceleration data was more symmetric around the abscissa than the strain data. Comparisons of fatigue damage estimates based on strain with and without mean stress correction factors showed negligible change in predicted life so the level of symmetry was determined to be not an issue. To determine if correlation exists between the two signals and whether relative magnitudes were equivalent, Root Mean Square (RMS) strain and RMS acceleration for 5 second intervals are plotted in Figure 5.3. Interval ranges between 0.5 and 20 seconds were investigated, but 5 second intervals were used to reduce scatter from wild points or spikes while retaining significantly different RMS values due to spatial changes in terrain.

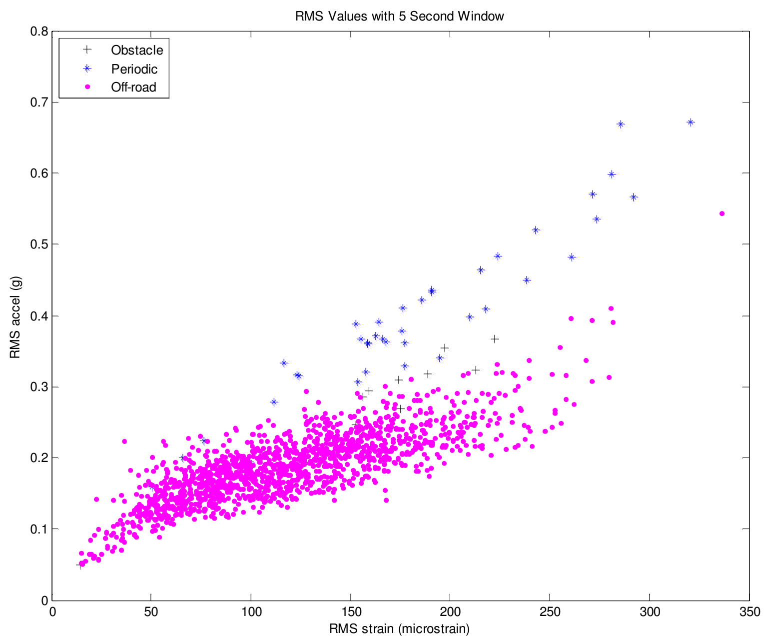

Figure 5.3: Sample strain and acceleration comparisons

There appears to be a linear correlation between RMS strain and RMS acceleration for each of the course types. This suggests that there is a relationship between the strain and acceleration signals and that the magnitude of individual time segments is proportional.

5.4 Fatigue Estimates

Analysis based on strain data is the most common approach for making mechanical component fatigue damage estimates. When strain is shown to be uniaxial, estimating damage is relatively simple computationally. Remaining life estimates can be made using rainflow cycle counting to separate individual stress cycles, Basquin's model to evaluate damage for each cycle and Miner's rule for damage summation. These algorithms are simple enough to be performed in real time with modest computational power and provide reasonably accurate results. A mean stress correction method can be used if significant preload exists, but for cases with fully reversed cycles and a low offset to stress, a mean stress correction model is an unnecessary complication.

The major difficulty in making accurate remaining life predictions with a HUMS is obtaining accurate predictions of the strain cycles at critical locations. To evaluate accuracy of strain predictions based on accelerometer data, fatigue damage was calculated from acceleration based models and compared to measured strain fatigue calculations using the same cycle counting, damage and summation algorithms. To evaluate the potential for using simple repeatable test courses or events to predict damage on complex realistic usage, the obstacle and periodic courses were used for developing relationships between measured acceleration and strain. The predicted damage on the severe off-road courses was then used to evaluate the accuracy of the acceleration based fatigue damage versus the measured strain fatigue damage typically used in high fidelity fatigue models.

5.4.1 Maximum Excursion Scaling

A simple approach for predicting strain from acceleration, assuming that the peaks that cause fatigue damage are proportional, would be to calculate a scale factor based on the ratio of the maximum excursion from zero. A small set of large cycles are often major contributors to terrain induced fatigue, so a scaling factor based on the largest peak was evaluated based on ability to provide accurate fatigue predictions. The absolute maximums for the sets of obstacle and periodic courses were calculated for the strain and acceleration data and the ratio of the absolute peak strain to absolute peak acceleration are the scale factors listed in Table 5.1. The high fidelity fatigue model based on measured strain predicted average damage per mile to equal 2.83E-04 for Course 1 and 6.80E-04 for Course 2. Accuracy factor was defined as the ratio of the strain based damage per mile to the acceleration based damage per mile in the cases where strain damage was larger than the damage predicted based on acceleration. In the cases where strain predicted damage was smaller than acceleration values, the accuracy factor was calculated as the ratio of the acceleration based damage to the strain based damage. Accuracy factors and predicted miles to failure based on acceleration data are shown in Table 5.1.

Table 5.1: Maximum excursion scaling

	Obstacle	**Periodic**
Scale Factor	362 microstrain/g	268 microstrain/g
Course 1 Acceleration Predicted Damage/Mile	2.22E-04	6.32E-05
Course 1 Accuracy Factor	1.3	4.5
Course 2 Acceleration Predicted Damage/Mile	6.63E-04	1.85E-04
Course 2 Accuracy Factor	1.0	3.7

In addition to the accuracy over the total course, it was desired to describe the accuracy of the model on individual segments. This provides confidence that the model predictions are unbiased and will not provide a systematic under or over-prediction. Data were segmented into similar size files for each of the off-road courses. Due to variations in vehicle speed, the course segments varied between 1.7 and 5.3 miles in length. Figure 5.4 graphically presents the strain and acceleration based average damage predictions for segments of the 15 total miles of Course 1 and 23 total miles of Course 2. The obstacle course based scale factor had relatively accurate predictions while the periodic course scale factor significantly over predicted on all of the course segments. Accuracy factors ranged from 1.0 to 1.4 for the obstacle course based scale factor and from 2.8 to 5.3 for the periodic based scale factor.

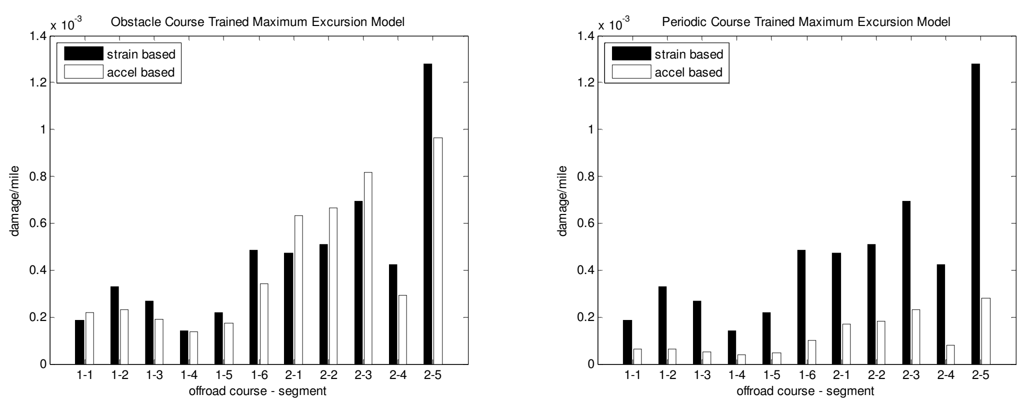

Figure 5.4: Maximum excursion model for terrain course segments

5.4.2 Fatigue Damage Based Scaling

A second method was evaluated which utilized fatigue damage directly as the basis for developing the relationship between acceleration and strain. A scale factor was calculated for each obstacle or periodic course acceleration time history such that the fatigue damage accumulated was equal to what was predicted from the strain values. Relative magnitude of individual cycles between strain and acceleration were disregarded in favor of forcing the fatigue damage estimate based on acceleration for each time history to match the corresponding fatigue damage from the strain. The average scale factor for the whole group of courses was then tested on each of the severe off-road courses. Table 5.2 shows results of the analysis.

Table 5.2: Fatigue life scaling

	Obstacle	**Periodic**	**Obstacle & Periodic**
Average Scale Factor	382 microstrain/g	282 microstrain/g	346 microstrain/g
Course 1 Accuracy Factor	1.0	3.6	1.5
Course 2 Accuracy Factor	1.2	2.9	1.2

Segments of the two severe off-road test courses were plotted in Figure 5.5. Periodic course based accelerometer models significantly over-predicted fatigue damage on each segment. The combination of obstacle and periodic course scale factors was significantly closer, but the scale factor determined from the obstacle courses gave the fatigue life estimates closest to the model based on strain measurements. Accuracy factors ranged from 1.0 to 1.4 for the obstacle course based scale factor and from 2.8 to 5.3 for the periodic based scale factor. Accuracy factors ranged from 1.0 to 1.7, 2.2 to 4.2, and 1.0 to 1.8 for the obstacle course, periodic course, and combination obstacle and periodic course based scale factor respectively.

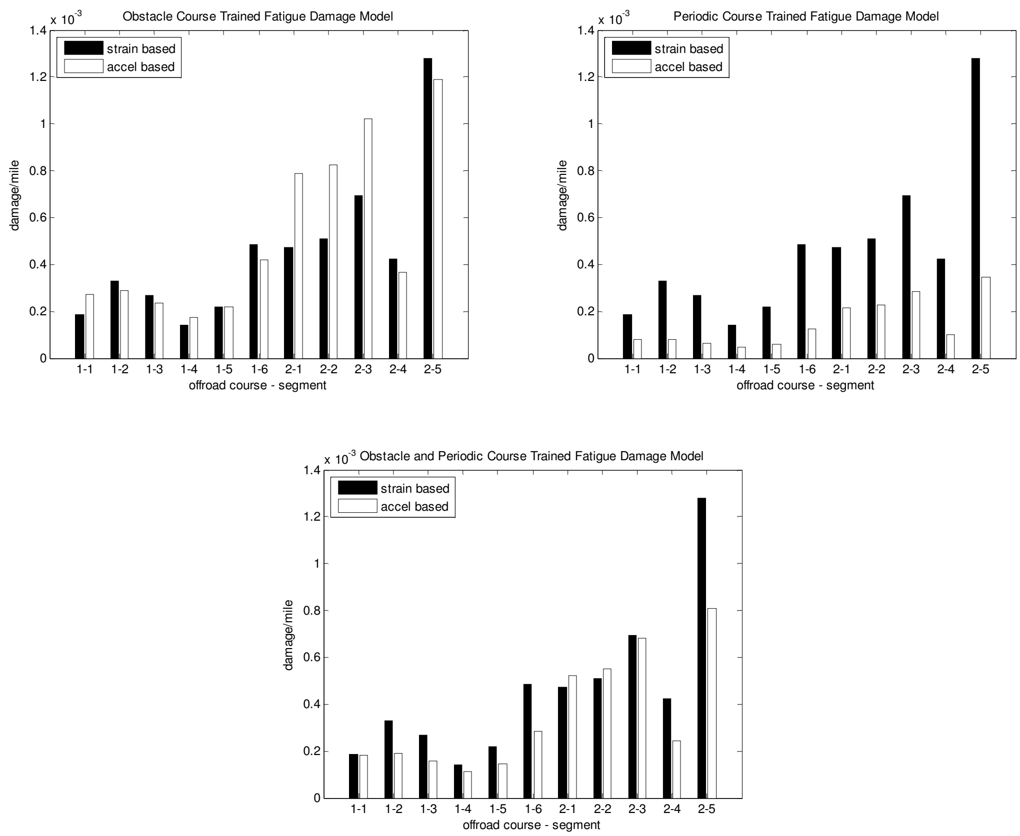

Figure 5.5: Fatigue damage based model for terrain course segments

5.4.3 Potential Improvements

Two processes to reduce the influence of high frequency low range cycles were evaluated based on their ability to improve fatigue damage estimates. The first was use of an 8th order, low pass, Butterworth filter at varying cutoff frequencies to remove the high frequency cycles. During data collection, accelerometer data was sampled at 2000 Hz and low pass filtered at 500 Hz, and strain data was sampled at 1000 Hz and low pass filtered down to 100 Hz. As would be expected, frequency analysis shows that the accelerometer data has more content 100 Hz and above. Filtering was successful in removing many of the high frequency cycles and tended to smooth and lower some absolute peaks slightly at high cutoff frequencies. Accuracy of fatigue life predictions showed minimal improvement filtering with cutoff frequencies between 500 and 100 Hz and a general deterioration in quality of predictions for cut off frequencies below 100 Hz.

The second process evaluated as a potential improvement was to remove cycles whose amplitude was below a certain level during rainflow cycle counting. The removal of ranges below 1 g had little effect on the overall accuracy of the predictions, generally degrading Course 1 predictions slightly and improving Course 2 predictions by a similar amount. Above 1 g, range removal showed significant deterioration in quality of all the predictions. Although range removal of cycles does not significantly improve fatigue, this process does have the benefit of reducing the computational power necessary to perform the fatigue prediction calculations. In situations where computational power is limited, this procedure may be worth pursuing.

5.5 Results

Accurate estimation of strain cycles was determined to be one of the most critical factors for application of a HUMS fatigue model based on acceleration. Two simple methods were proposed to determine a scale factor for relating measured acceleration to strain at a critical location. The scale factor was evaluated based on the resulting accuracy of fatigue predictions when compared with predictions from a high fidelity fatigue model using strain at a critical location. Tables 5.1 and 5.2 show that the accuracy for both models from a fatigue standpoint were an improvement on those expected from terrain identification models [15]. Of the two methods for determining a scale factor, fatigue life scaling was determined to provide more accurate fatigue predictions independent of the training course used. In addition, fatigue damage scaling is more robust due to the fact that it utilizes more data points. The maximum excursion method could be significantly skewed by a single unrecognized wild point during training. The fatigue damage scaling method could also be affected by outliers or spikes in the measurement, but the peaks of all the cycles that cause damage contribute to the scale factor. Potential improvements to more closely match the cycle counts between strain and scaled acceleration were investigated, but determined to provide little improvement to the damage estimation model.

Two types of simple, repeatable test courses were evaluated based on the ability to relate acceleration to strain for accurate prediction of fatigue damage on severe off-road courses. Training on the courses containing half-round obstacles provided more accurate predictions of fatigue damage than the periodic courses. Figure 5.3 shows that throughout the RMS strain ranges, obstacle data more closely match the off-road courses. At high values of strain RMS, which likely contributes the most to damage estimations, much higher acceleration RMS was measured for the periodic courses than the obstacle or off-road courses. Under-prediction of strain would result in the systematic under-prediction of fatigue damage manifested in the periodic course damage predictions of Figures 5.4 and 5.5. Half round obstacles are recommended for developing acceleration to fatigue relationships for offroad courses based on this limited data set. More analysis and testing are needed to verify if similar events provide suitable relationships for different components, vehicle systems, and courses.

5.6 Conclusions

A model has been proposed to provide remaining life estimation based on vibratory measurements from an accelerometer. While strain is typically the desired input to a fatigue model, acceleration sensors are less susceptible to damage from the military ground vehicle environment and provide more reliable data. Acceleration measurements may also provide information pertaining to the inputs of multiple components or multiple locations rather than being limited to a single critical area. A simple scale factor was determined to be sufficient to relate acceleration and strain for a sample component. Two methods for the determination of an appropriate scale factor were evaluated, and calculating the scale factor required to set damage predictions from the acceleration data equal to strain based predictions at the critical location for a number of half round obstacles was selected as superior.

It was shown that fatigue damage accuracy for both models and all terrain courses were improved compared to those expected from terrain identification models [15]. This model was also shown to require far less training data to develop relationships suitable for fatigue estimation, but simultaneous strain and acceleration data are necessary to develop the appropriate scaling and to test the accuracy of predictions. Computationally, the model developed here is more intensive than a terrain identification model in that it requires the use of rainflow cycle counting, Basquin's model and Miner's rule for damage summation for each component monitored. For critical components and safety related equipment, the extra computational power may be justified for the improved accuracy of the fatigue predictions.

Chapter 6: Identifying Damage Indicators and Physics-Based Strain Estimation

In this chapter, methods for identifying good indicators of strain from a wide variety of sensor data for a multiaxial load case were investigated. Physics based subsystem models are also developed and compared based on the improvement in fatigue damage prediction capability. A baseline physics of failure analysis was performed on an example component to evaluate the proposed HUMS algorithms and demonstrate the accuracy of the resulting fatigue predictions (See Appendix A). The remainder of material in Chapter 6 is presented as it was formatted for submission in a technical journal and contains repeated background information. To avoid repeated information, readers should skip to the last paragraph in section 6.1.

6.1 Background

In a fiscally conscious environment, reliability is always a critical consideration in the design and manufacture of products. For many items designed to be used over a long time span, operation and support represents a larger proportion of the total cost than procurement. Reliability directly affects the logistics burden associated with a particular piece of equipment and is a major driver for operations and support cost. This is the case for many military vehicles, but military vehicle designers have additional incentive to design reliable equipment. Failure of components or subsystems results in inconvenience for civilian users of products, but soldier safety and effectiveness are often dependent on the operability and performance of their vehicles. Maintaining operation of the critical functions and subsystems is essential to the completion of the difficult and dangerous missions assigned to military personnel.

Even though reliability is typically assigned a high level of importance during the development and selection of Army equipment, the Government Accountability Office reports that some major systems still have reliability issues. One technology that is being promoted in the Department of Defense is the inclusion of Health and Usage Monitoring Systems or HUMS within a vehicle platform. HUMS can be practically defined as a system of sensors, processors and algorithms that give an indication of remaining component life. These systems monitor the usage of individual vehicles and record the effect of the environmental factors on specific components. Remaining life prognostics is the process of converting the usage data into predictions of the probability of failure for components. The resulting predictions can be processed and provide information to operators, maintainers, and mission planning personnel as to which components should be serviced, what repair parts are likely to be needed at a maintenance facility, and which vehicles have the lowest probability of failure during a mission. With good management, this information can be used to increase availability and reliability, while decreasing overall maintenance and system cost.

An often overlooked ancillary benefit of a successful health and usage monitoring system is that it can provide an indication of what the past usage of the vehicle has been. During the development of a military vehicle system, designers often must use generalized, qualitative descriptions to predict usage and load inputs. Specific information on previous generation vehicles is often unavailable or infeasible to attain. Testing of these systems is based on estimations of previous vehicle usage and worst-case scenarios because more realistic estimates are unavailable. Data collected for critical components from a HUMS over the lifetime of multiple vehicles would provide the information necessary to make statistically significant estimations of the likely usage of next generation vehicles.

The concept of a HUMS is not particularly novel. The costs associated with development and purchasing, along with the detailed information of the system necessary to perform health and usage monitoring, typically limit application to critical components within expensive systems that are subjected to relatively simple environmental and loading conditions and operated over long time spans. Many of these applications have been for large static systems with a limited number of relevant loading conditions such as manufacturing and power facilities (Li 1995, Jarrell 2006), bridges (Gandhi 2007), elevator systems (Yan 2005), and computer servers (Schuster 2004.) Applications of HUMS to military vehicles have been primarily on fixed-wing aircraft ("Prognostics..." 2004, Trammel 1997, Hunt 2001, Mourna 2006, Martin 1999) and rotorcraft (Ellerbrock 1999, Evans 2002, Bechhoefer 2004, Gordon 1991.)

The relevancy of the techniques and processes developed for these applications to a military ground vehicle is limited. These examples are exposed to environments and loading conditions that have significantly less variation than those of a typical ground vehicle. In order to address all the relevant load cases on a ground vehicle system, robust engineering models are needed to calculate damage accumulated. Use of air and rotorcraft techniques on a military ground vehicle is also a challenge due to the fact that the life cycle costs associated with these applications justify the development of complicated HUMS. The development and unit cost of a HUMS applied to a military land vehicle would need to be much less. The cost to develop a military ground vehicle system is often several orders of magnitude less than that of an aircraft, so expenditures for the development of a HUMS would have to be reduced by a relative proportion. In addition, cost of the HUMS could not be a significant portion of the total vehicle cost. Redesign of components or replacement of the entire system may be a preferred alternative if the unit cost of a HUMS is prohibitive.

Recently, work has been performed to address some of the inherent challenges in applying HUMS and remaining life prognostics to ground vehicle systems. HUMS for sensors and actuators for the commercial auto industry (Barone 2006, Ng 2006) and rotating components within the turbine engine of an M1 Abrams tank (Greitzer 2002) have been a focus of ongoing research. To address terrain induced fatigue, a general set of algorithms for the application of a HUMS to a military ground vehicle was developed (see Chapters 3 and 4). Durability and fatigue testing are often performed based on an anticipated usage on primary, secondary and off-road terrains because the loading on many of the components changes significantly for each terrain type. These algorithms take advantage of the similarity of damage rates within each terrain type to estimate fatigue damage accumulated on individual components. One of the major advantages of this system is that a very simple set of sensors and algorithms provide damage estimates for multiple components. This effectively spreads the developmental and unit cost of the HUMS across many components.

Accuracy of fatigue damage predicted from the recommended terrain identification algorithms for sample components varied by a factor of 2.9 to 6.8 of the damage predicted by high fidelity fatigue models. These results are within the typical error of fatigue estimates for similar components subjected to widely varying vibration inputs, but accuracy was shown to be highly dependent on identifying a fatigue damage per exposure time scale factor that is representative for all conditions within a terrain type. This requires significant testing on multiple courses that would represent the full range of scenarios that a military vehicle would encounter.

The desire for a more accurate fatigue estimate and the ability to minimize required algorithm training data may justify more complex algorithms for critical or safety related components. A model was developed that used vibratory inputs from an accelerometer to make component fatigue predictions on a military wheeled vehicle system (see Chapter 5.) While this type of model requires significantly more computational power, it could work in concert with terrain identification algorithms to provide enhanced fatigue damage predictions and minimize the algorithm training data necessary. Accuracy of fatigue damage predicted from the recommended algorithms for a sample component was shown to vary within a factor of 1.0 to 1.4 of the damage predicted by a high fidelity fatigue model. While these were significant gains in accuracy, the algorithms developed apply only to the special cases of simply loaded components where the measured acceleration has a waveform similar to the measured strain. More computationally intensive algorithms may be required to perform remaining life prognostics on more complexly loaded components.

The objective of this research is to investigate the feasibility of using data collected from a limited set of existing and simple add-on sensors to make fatigue damage estimations on a complexly loaded component of a military wheeled vehicle system. Methods for identifying the critical inputs for fatigue estimation are evaluated. While this research was meant to develop principles generally applicable to HUMS and remaining life prognostics for a multiaxial case, in order to better illustrate the principles, a demonstration vehicle and component were chosen. A baseline physics of failure analysis was performed on the demonstration component to evaluate whether the proposed HUMS algorithms are appropriate and to demonstrate the accuracy of the resulting fatigue predictions (See Appendix A).

6.2 Demonstration Vehicle and Component

An eight wheeled Army vehicle similar to the one shown in Figure 6.1 was utilized as the demonstration vehicle for this research. Data were collected from candidate sensors for the HUMS. These included accelerometers on the sprung mass of the vehicle, Global Positioning Satellite (GPS) data, J1708 bus data, and suspension position via the built-in Height Management System (HMS) sensor. Data from a triaxial strain gauge rosette was also collected on an example component over multiple courses at the Yuma Proving Ground. Course data collected were separated into distinct sets that could be used for training and testing of algorithms. Specific details of the test courses will not be discussed, but each set included at minimum one test course described as primary, secondary and off road.

Figure 6.1: Army wheeled vehicle

The primary failure mechanism for the example component was multiaxial fatigue due to a combination of terrain and powertrain induced loading inputs. Two legs of the triaxial strain gauge rosette labeled Strain 1 and Strain 2 were generally attributed to terrain induced loading through the suspension system. The leg labeled Strain 3 was attributed to torque produced through the drivetrain. A high-fidelity multiaxial fatigue analysis was performed using commercially available software on the strain data measured on the example component for each course. Results of the fatigue analysis were verified anecdotally based on failure rates. Further details regarding the example component have been intentionally obscured to minimize available information on failure modes of military equipment. It is the purpose of this work to present the method for application of remaining life prognostics algorithms and details of the exact component are unnecessary.

6.3 Direct Strain Model

Strain measurements are desirable as an input to fatigue damage estimation models. However, the common method of measuring strain with adhesively bonded, electric resistance wire strain gauges is fraught with difficulties. This type of strain gauge is sensitive to temperature variations, and bonding can be an issue if the gauge is expected to last the life of the component. A preferable approach would be to use more rugged sensors to predict strain on the critical component. Use of sensors already integrated within the vehicle is an ideal source from which to estimate strain. These sensors typically have high reliability due to their use in other vehicle subsystems and the cost of integrating them within the HUMS is minimal in comparison with the cost of adding an additional sensor. Sensors such as accelerometers and GPS units are robust, easy to apply and make a good alternate source if the integrated sensors do not provide data suitable for predicting strain. In order to evaluate the candidate sensors based on their ability to make fatigue damage estimations on a complexly loaded component, two statistics are compared.

6.3.1 Normalized Cross-Correlation

Cross-Correlation is a standard method for estimating the degree to which two signals are correlated. The cross-correlation (r_{xy}) of two series x(i) and y(i) is defined in equation 1 where $\bar{x}$ and $\bar{y}$ are the means of the corresponding series and d is the time lag.

$$r_{xy} = \frac{\sum_i \left[(x(i)-\bar{x})(y(i-d)-\bar{y})\right]}{\sqrt{\sum_i (x(i)-\bar{x})^2}\sqrt{\sum_i (y(i-d)-\bar{y})^2}} \qquad (1)$$

The cross-correlation can be normalized by the auto-correlation which is simply the value of the cross-correlation of a signal with itself under no time shift. Normalized cross-correlation values were calculated for each of the courses with no time shift. It was hypothesized that a signal on another part of the vehicle may give a good indication of the strain at the critical area, so the maximum normalized cross-correlation was also calculated within a time shift of 0.5 seconds. The average normalized cross-correlation for the training courses with zero and a maximum of 0.5 second lag are listed in Table 6.1. The candidate sensor with maximum values of average normalized cross correlation for the strains attributed to terrain induced loading (Strain 1 and Strain 2) and the drivetrain torque (Strain 3) were selected for fatigue damage estimations and are labeled in bold font. Including a delay made relatively minor changes to the average cross-correlation values, although the 0.5 second lag did result in the selection of a different input channel for Strain 3.

Table 6.1: Average normalized cross-correlation with strain

Channel	**Strain 1 Average Normalized Cross-correlation with, without lag**	**Strain 2 Average Normalized Cross-correlation with, without lag**	**Strain 3 Average Normalized Cross-correlation with, without lag**
Battery Voltage	0.01, 0.01	0.01, 0.01	0.01, 0.01
Engine Temperature	0.01, 0.01	0.01, 0.01	0.01, 0.01
Engine Speed	0.01, 0.01	0.02, 0.02	0.03, 0.03
Instant Fuel Economy	0.16, 0.13	0.05, 0.04	**0.36**, 0.31
Percent Accelerator Pedal Position	0.09, 0.08	0.03, 0.03	0.23, 0.20
Percent Engine Load	0.07, 0.07	0.03, 0.03	0.14, 0.13
Transmission Oil Temperature	0.01, 0.01	0.01, 0.01	0.01, 0.01
Transmission Output Shaft Speed	0.02, 0.02	0.02, 0.02	0.06, 0.05
Fuel Rate	0.08, 0.07	0.03, 0.02	0.22, 0.19
Vehicle Speed	0.04, 0.03	0.02, 0.02	0.07, 0.06
Sprung Accel Front Left Side	0.14, 0.07	0.10, 0.05	0.14, 0.05
Sprung Accel Rear Left Side	0.19, 0.19	0.17, 0.16	0.12, 0.10
Sprung Accel Rear Right Side	0.22, 0.21	0.19, 0.18	0.15, 0.13
HMS Axle 1 Left Side	**0.33, 0.32**	0.27, 0.26	0.36, 0.32
HMS Axle 1 Right Side	0.21, 0.17	**0.33**, **0.31**	0.21, 0.17
HMS Axle 3 Left Side	0.32, 0.30	0.30, 0.28	0.36, **0.35**
HMS Axle 3 Right Side	0.18, 0.18	0.30, 0.29	0.16, 0.16

A linear scale factor and offset for each of the training data sets were calculated such that the maximum and minimum values measured for the candidate sensor matched maximum and minimum of the measured strains. The mean scale factor and offset across all the training data sets was then utilized to test the accuracy of the fatigue predictions. It was previously demonstrated that scaling based on fatigue life was more accurate than maximum excursion for a uniaxial fatigue case, but for a multiaxial case the equations were indeterminate (See Chapter 5). Life predictions were made based on candidate sensor strain predictions utilizing the same fatigue analysis software and equations used in the high fidelity fatigue estimates. Results from the training data sets were labeled 1-5 and the testing data sets were labeled A-D for the scaled candidate sensors. Values were plotted and compared to the high fidelity fatigue model results in Figure 6.2.

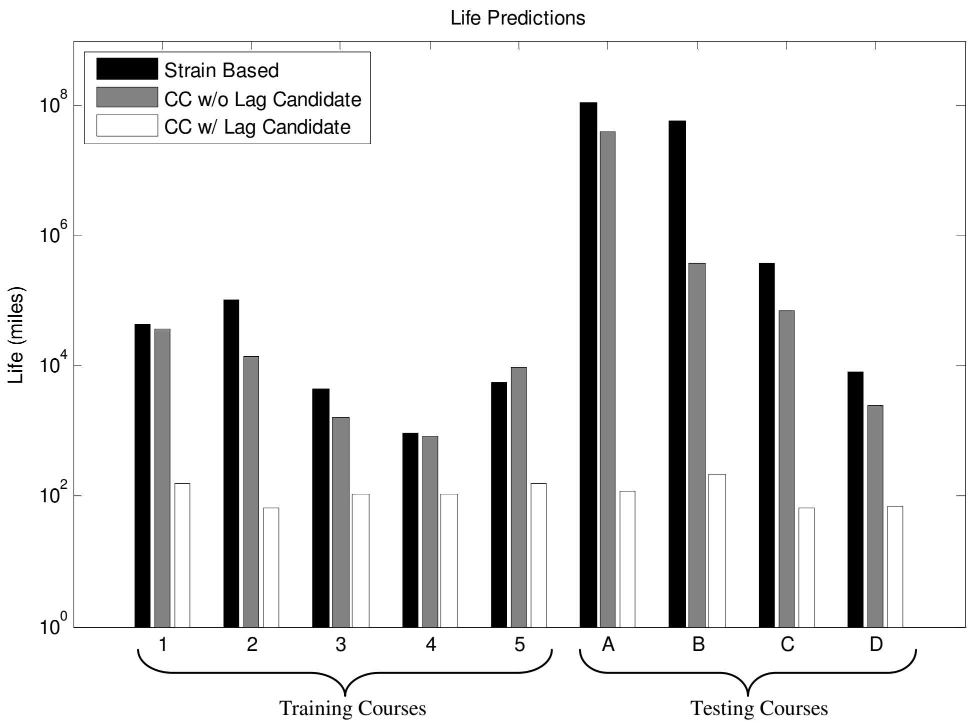

Figure 6.2: Life estimate using Cross-Correlation (CC)

6.3.2 Coefficient of Determination of Root Mean Square

A comparison of Root Mean Square or RMS values for linearity was used previously to determine if relative magnitude of individual time segments are proportional [20]. Relative magnitude of strain cycles are essential to calculating fatigue, so a process was developed to evaluate the linearity of the comparison. Strain and predictor channels were separated into five second blocks. RMS, denoted as z in equation 2 below, was calculated for each time sample of the strain or predictor channel (x_i) in the block.

$$z = \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^{\ 2}} \tag{2}$$

The coefficient of determination (R^2) was then calculated based on the RMS values (z), a least squares, linear fit of the sensor RMS blocks to the strain RMS blocks ($\hat{z}$) and the average sensor value ($\bar{z}$).

$$R^2 = 1 - \frac{\sum_i (z_i - \hat{z}_i)^2}{\sum_i (z_i - \bar{z})^2} \tag{3}$$

Resulting coefficient of determination values for each sensor are listed in Table 6.2 with the maximum values in bold font.

Table 6.2: Coefficient of determination of RMS with RMS strain

Channel	**Strain 1 Average R^2 RMS**	**Strain 2 Average R^2 RMS**	**Strain 3 Average R^2 RMS**
Battery Voltage	0.01	0.00	0.01
Engine Temperature	0.01	0.03	0.03
Engine Speed	0.04	0.04	0.06
Instant Fuel Economy	0.03	0.01	0.07
Percent Accelerator Pedal Position	0.02	0.01	0.03
Percent Engine Load	0.10	0.06	0.07
Transmission Oil Temperature	0.03	0.04	0.02
Transmission Output Shaft Speed	0.05	0.05	0.16
Fuel Rate	0.03	0.01	0.04
Speed	0.04	0.05	0.14
Sprung Accel Front Left Side	0.15	0.10	0.01
Sprung Accel Rear Left Side	0.17	0.12	0.03
Sprung Accel Rear Right Side	**0.18**	**0.13**	0.05
HMS Axle 1 Left Side	0.10	0.11	0.16
HMS Axle 1 Right Side	0.09	0.12	0.10
HMS Axle 3 Left Side	0.11	0.11	**0.19**
HMS Axle 3 Right Side	0.03	0.04	0.06

A linear scale factor and offset for each of the training data sets were calculated such that the maximum and minimum values measured for the candidate sensor matched maximum and minimum of the measured strains. The mean scale factor and offset across all the training data sets was then utilized to test the accuracy of the fatigue predictions. Life of the scaled candidate sensors were plotted and compared to the high fidelity fatigue model results in Figure 6.3.

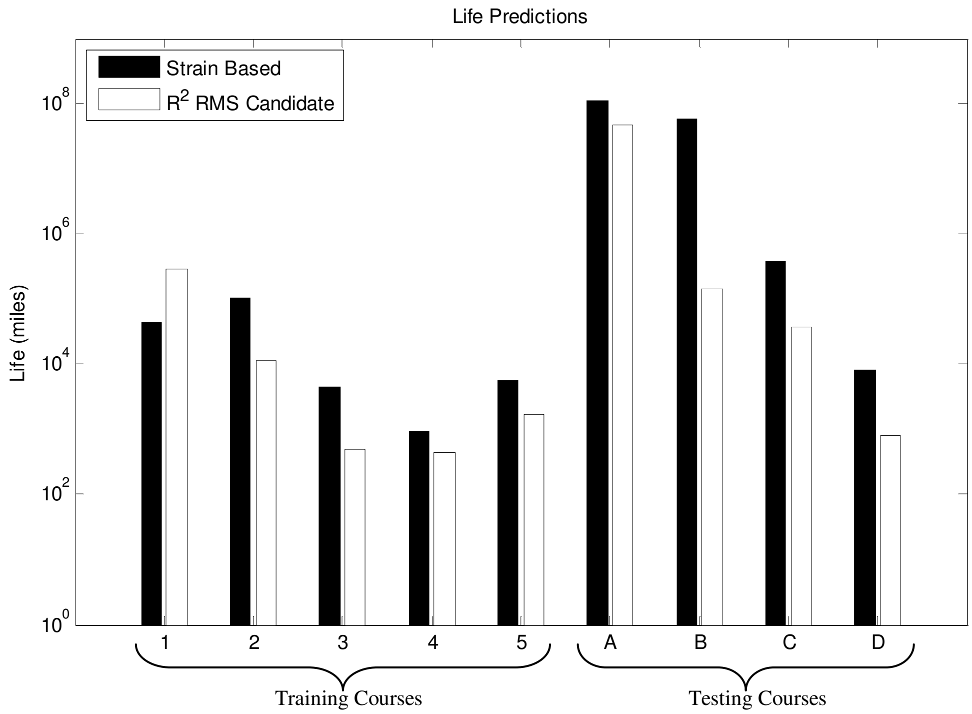

Figure 6.3: Life estimate using coefficient of determination of root mean square

6.4 Physics-Based Estimation

As an alternate method to utilizing statistics to blindly select from a pool of candidate sensors to estimate strain at a critical location, a physics-based estimation could be made utilizing known characteristics of the vehicle subsystems. Candidate sensors are not typically available that provide all the information desired for a highly accurate load model of critical components, nor is it feasible to run a highly complex model real-time on an inexpensive HUMS. If a basic model using a limited set of sensors can be manipulated to provide the most critical aspects of loading, a physics-based load estimation may be justifiable.

To evaluate this method on the demonstration component used in this study, it was necessary to estimate the torque applied through the drivetrain subsystem in order to predict Strain 3 and the terrain induced loads through the suspension subsystem to predict Strain 1 and Strain 2. A simplified drivetrain model was developed which utilized engine speed, vehicle speed and a simplified shift map to estimate engine load inputs. Transmission output shaft speeds, component geometries, and material properties were used to estimate the resulting reaction torques and convert load information to strain at the critical area. A simple suspension model was developed based on sprung and unsprung masses, sprung mass acceleration near the example component and unsprung mass acceleration via differentiated HMS reading. Strain predictions were implemented into the multiaxial fatigue model and compared to the high-fidelity fatigue predictions. Physics-based predictions were shown to be significantly less accurate for the example component than the estimates made based on the blind sensor selection. This may be attributable to the simplifications necessary to make the physics-based models run in real-time, the limited set of sensors, the locations from which the subsystem load predictions were made or the fidelity of the sensor data.

6.5 Hybrid Models

To investigate the poor quality of the physics-based predictions, the average normalized cross-correlation and coefficient of determination of root mean square statistics were calculated for the physics-based strain predictions to determine which subsystem model resulted in the significantly less accurate fatigue predictions. In general, the loading seen in Strain 1 and Strain 2 were attributed to the terrain induced loading through the suspension subsystem and Strain 3 was attributed to the drivetrain. Results are shown in Table 6.3.

Table 6.3: Physics-based comparison

Estimator	Strain 1 Average	Strain 2 Average	Strain 3 Average
Average Normalized Cross-Correlation with Lag	0.03	0.03	0.15
Average Normalized Cross-Correlation without Lag	0.03	0.03	0.14
R^2 RMS	0.14	0.10	0.07

Average normalized cross-correlation statistics suggest that the powertrain subsystem model was the cause of the poor predictions, while the coefficient of determination of root mean squares suggests the suspension model was the issue. Two hybrid models were developed. Hybrid Model A utilized the physics-based suspension model to predict strains 1 and 2. Strain 3 was predicted based on the average normalized cross-correlation statistic without a time lag candidate sensor. Hybrid model B utilized the physics-based powertrain model to predict strain 3 and the average normalized cross-correlation without lag statistic candidate for strains 1 and 2. Both models showed improvement over the physics-based strain estimation model, but the Hybrid B model gave the most accurate fatigue predictions. Life predictions based on the Hybrid B model were plotted and compared to the high fidelity fatigue model results in Figure 6.4.

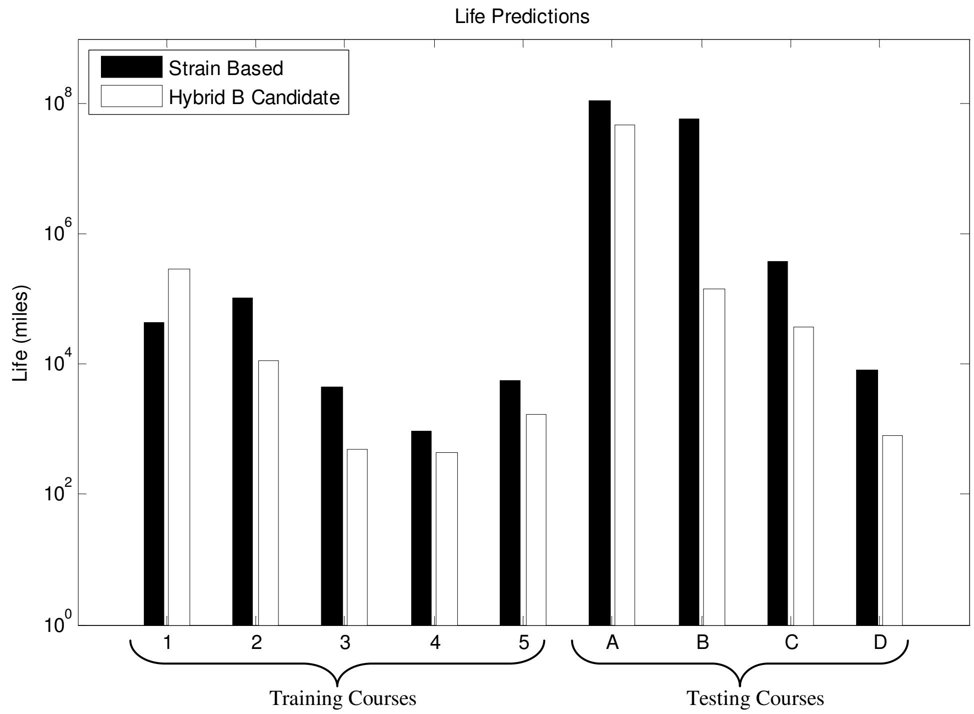

Figure 6.4: Life estimate using Hybrid B model

6.6 Results

As would be expected the life estimated on the training courses and shown in Figures 6.2, 6.3, and 6.4 were fairly accurate. In order to compare the accuracy of various models on the testing courses, a representative usage made up of the available terrain types was necessary. Requirements documents indicate a predicted usage in terms of primary, secondary and off-road courses for each variant of the demonstration vehicle. Durability tests for army combat vehicles are commonly 20,000 miles in length. Predictions of the fatigue damage accumulated over a 20,000 mile test following the expected terrain profile for the most common variant were made based on the testing data sets A-D for each model. Results are listed in Table 6.4. As a point of comparison, the most accurate terrain identification models resulted in 20,000 mile damage accumulated of 1.79 to 3.00 for similar components (see Chapters 3-4).

Table 6.4: 20,000 mile endurance test damage

Model	20,000 Mile Damage Accumulated
High Fidelity Strain	0.75
Normalized Cross-Correlation without Time Lag	2.57
Normalized Cross-Correlation with Time Lag	216.44
R^2 RMS	7.80
Physics-Based	0.00
Hybrid A	0.21
Hybrid B	1.28

Normalized cross-correlation without time lag provided the closest estimate to the high-fidelity strain-based damage of the direct strain estimate models. Allowing a maximum time shift of 0.5 seconds made no difference in the selection of sensors for strains 1 and 2, but the time shift led to the selection of the instant fuel economy calculations rather than the left side, axle 3 HMS sensor for strain 3 predictions. Close review of the instant fuel economy data showed that the data was clipped at a maximum value. When this data was scaled based on the maximum excursion, all of the clipped cycles were equivalent to the maximum strain cycle. This led to the significant under-prediction of life seen in both the training and testing data in Figure 6.2 and the over-prediction of damage seen in Table 6.4. Although this was not readily apparent from the cross-correlation data alone, the R^2 RMS showed significantly higher correlation between strain 3 and axle 3 HMS sensor data. If a direct strain model is selected for a component, it would be advisable to calculate both statistics in order to select the most appropriate candidate sensors. An alternate method of determining the scaling and offset based on fatigue rather than the maximum excursion may also improve fatigue predictions for the direct strain models.

The physics-based model developed required significantly more computational power and had poor predictive capabilities due to the limited ability of the suspension model developed to predict strains 1 and 2. When the normalized cross-correlation without time lag model for predicting strains 1 and 2 was combined with the powertrain model for predicting strain 3 in the Hybrid B model, the damage estimate over the 20,000 mile endurance test was much improved. This demonstrates that the use of a physics-based model can improve fatigue damage predictions if the component monitored justifies the additional computational load. Failure of the suspension model is attributed to the lack of quality sensor data at the critical locations necessary to make a high fidelity strain prediction. Sensor data may not be of the quality required to make accurate predictions in current vehicles, but inclusion of higher quality sensors at critical locations may be justifiable for future vehicles designed for use with HUMS and remaining life prognostics.

6.7 Conclusions

In order to utilize HUMS and remaining life prognostics to obtain the desired improvements in reliability and availability on military ground vehicles within a reasonable cost, durable sensors that provide loading information for fatigue sensitive components are critical. Strain is often the desired input for fatigue calculations, but most common sensors used to measure strain including adhesively bonded electric resistant wire strain gauges, are neither rugged nor reliable enough for a military ground vehicle environment. In addition, the sensors need to provide data for many of the components on a vehicle. Components susceptible to fatigue damage that should be monitored using a HUMS are not clearly recognized during the design of a vehicle system, so sensors that indicate loading to a wide variety of components are preferred. Use of sensors already integrated within the vehicle is an ideal source from which to estimate strain due to their high reliability and minimal additional cost. Add-on sensors such as accelerometers and GPS units are robust, easy to apply and make a good alternate source for strain estimates. For many modern military vehicles, the combination of integrated and add-on sensors make a large group of candidates available for use in a HUMS, but the best indicators of strain may not be clearly identifiable. A method is needed to identify and select sensors that provide inputs suitable for fatigue damage models.

Two statistics were evaluated based on ability to identify data that provides accurate fatigue predictions for a complexly loaded component on a military wheeled vehicle. Normalized cross-correlation without time lag provided the most accurate fatigue estimate of the direct strain calculations. Allowing for time shift was shown to have a minor effect on the ranking of candidate components, but calculation of the coefficient of determination of root mean square statistics as an additional means of comparison are recommended for identifying the best candidate sensor.

As an alternate method to utilizing statistics to select sensors that indicate strain on a component, a physics-based estimation can be made from the sensor data available and known characteristics of the vehicle subsystems. More complex physics-based subsystem loading models and geometry data were shown to improve the fidelity of fatigue predictions, but quality sensor data at critical locations is essential. Generally an improvement in the accuracy of fatigue predictions was demonstrated as the HUMS and remaining life prognostics algorithms increase in complexity. Selection of the model to be used on a specific component requires a balance of the accuracy needed with the developmental and computational cost.

Chapter 7: Discussions and Summary

The goal of this research was to demonstrate that HUMS and remaining life prognostics are feasible for military wheeled vehicles and develop methods to assist in their application. Wheeled vehicles have many characteristics which make application of HUMS a challenge. Foremost among these are the large number of unique components that have complex loading profiles and are relatively inexpensive. Methods for application and appropriate algorithms are necessary to enable a balance of accuracy of the remaining life estimates with development complexity, computational power required and cost.

Incorporating HUMS into a military vehicle life cycle is also a worthy goal. Military ground vehicles typically go through a series of distinct phases during development, testing, operation and disposal that are marked by key milestones and tests. Incorporating HUMS architecture with the military vehicle life cycle would allow designers to take advantage of required phases and tests to tune models and minimize any detriments to the cost or schedule caused by HUMS implementation. Methods and algorithms that are designed to take advantage of the military life cycle would increase the likelihood of a successful HUMS.

This research was successful in demonstrating that HUMS are a viable technology for improving the reliability and availability of military wheeled vehicles. Fatigue of metal components is a common failure mode on military vehicles, and failures of this type have a major effect on vehicle reliability and availability. Algorithms specific to predicting damage accumulated through metal fatigue were developed that could be reasonably computed real-time as part of an on-board, inexpensive HUMS. Methods for identifying critical data and instrumentation were also described. The methods and algorithms were demonstrated for a variety of components on a military wheeled vehicle, and validation was performed by comparing the results of the remaining life prognostics with those from high fidelity physics of failure models.

7.1 Model Fidelity

To apply a HUMS to relatively inexpensive equipment such as military wheeled vehicles, reasonable limitations must be applied to the hardware to minimize cost. Resources for computation and processing must be used economically. For a HUMS with limited computational resources, model fidelity and complexity are critical issues. The case studies developed in Chapters 3 through Chapter 6 showed that accuracy is roughly correlated with model complexity. Generally, as the computational power that a fatigue damage model requires increases, the estimates of damage accumulated become more accurate. The simplest computational models were discussed in Chapters 3 and 4. These models utilized a feature recognition technique to identify terrain or usage conditions and assign damage for time exposed. A single set of algorithms based on a simple statistic provides monitoring for all the components subjected to a particular loading condition. Additional scale factors would attribute the load appropriately to other components and allow damage accumulation to be calculated for these components with little increase in computational complexity.

More computationally intensive models that predict strain at a critical location from robust sensor data were introduced in Chapters 5 and 6. Predicted strain is used to calculate fatigue damage accumulated through rainflow cycle counting, Basquin's equation, and Miner's damage summation rule. These algorithms require more computational power, but are simple enough to be used real-time. Results are limited to a single failure mode of a single component. Removal of cycles based on amplitude and frequency were evaluated based on ability to enhance prediction capability in Chapter 5, but these techniques required additional computations and showed little improvement in fatigue damage prediction.

The highest fidelity models were demonstrated in Chapter 6 and utilized detailed physics-based subsystem models or a combination of physics-based and direct strain models that would account for the individual loads applied to a component. Subsystem models were used to calculate the dynamic loading for a component, and mechanics of materials were used to predict strain at the critical location for each time step. Similar methods to those used in the direct strain models were leveraged to calculate damage accumulated and life remaining. The vehicle subsystem models developed may be able to provide loading information to other components being monitored, but they also require many inputs in order to provide accurate loading conditions. Mechanics of materials models also can be computationally intensive to convert the loads to strain at the critical area. These models are geometry and failure mode specific, so each component monitored would require a unique mechanics of materials model. For the example component in Chapter 6, the subsystem and mechanics of materials models required significant computational resources. Only a limited number of components could be modeled with this degree of fidelity on a reasonably priced HUMS.

As potential components on a vehicle that could be monitored by HUMS are discovered, it will become necessary to evaluate tradeoffs between cost of the HUMS, level of fidelity, and number of components monitored. A number of elements must be known to determine which models provide optimal returns on total vehicle reliability and availability.

From a vehicle standpoint there are limited resources from which to perform damage calculations. The number of components that will be monitored, the failure modes of the monitored components, and the resources available are key inputs for optimizing the HUMS and selecting damage models. Most vehicles have some limited computational power for onboard systems currently, and vehicles that are integrated with HUMS would likely have additional processing available or could be expanded to have additional capability. The cost for adding computational power and any limits imposed by size, electromagnetic interference, thermal load, and weight are critical for optimizing HUMS results and selecting the most appropriate models for a component. Representative estimates of usage are needed to calculate the return from a HUMS model. In Chapters 4, 5 and 7, estimated usage from requirements documents was used to evaluate model accuracy based on a realistic usage profile. As HUMS are implemented on vehicles, data collected can be used to make statistically significant estimations of the likely usage of vehicles rather than approximations based on requirements documents.

Information specific to the failure mode and component is also critical to determining the optimal models. In order to select the appropriate HUMS model for a particular component failure, several component specific items need to be investigated. Criticality of the failure is important because highly critical components can have a detrimental effect on a large number of subsystems. If the component is directly related to the safety of the operators, additional emphasis and accuracy may be required for the prognostic model. A component that is particularly expensive or whose failure leads to damage of expensive components may justify a higher level of fidelity. Recovery and repair time in case of failure also affect component criticality. Computational resources must be weighed and compared with the criticality of components and the resources required to develop models in order to determine the optimal HUMS solutions. Model fidelity for a particular component must be determined by allocating resources based on criticality of the component, and the effect on soldier safety, system reliability and system availability.

In order to determine the most appropriate model and level of fidelity to utilize, a number of component, vehicle, and failure mode specific inputs need to be weighed versus the HUMS properties. To achieve the best returns in terms of reliability and availability improvements, potential accuracy of predictions needs to be compared and representative estimates of usage determined in order to select the most appropriate models.

7.2 Instrumentation and Sensors

Another key aspect for developing HUMS and remaining life prognostics is selecting potential sensors that may be appropriate for the models and identifying which sensors provide the inputs necessary to predict damage. In general, any sensors used need to be reliable enough that the HUMS would not contribute significantly to the total platform malfunctions. Frequent need for replacement or calibration requiring human interaction would increase the logistics and maintenance footprint of a vehicle and be counter to the goals of any HUMS. Physical or analytical redundancy can improve the reliability and availability of instrumentation, but redundancy needs to be balanced with the additional cost. Methods for selecting the appropriate sensor data for damage models may also be required in cases where appropriate indicators are not clearly identifiable.

7.2.1 Potential Sensors

A military ground vehicle provides a particularly difficult environment for instrumentation and sensors. Military ground vehicles typically experience rough terrain, extreme temperature changes, frequent exposure to dust and other contaminants, and large fluctuations in humidity which are all detrimental to many sensors. The focus of the models developed in this research is fatigue damage in metals. This is a common mode of component failure for military wheeled vehicles. Strain measurement is the typical input to fatigue damage models. The most common method of measuring strain is through the use of adhesively bonded strain gauges, but this is difficult because strain gauges are sensitive to environmental effects seen in a military wheeled vehicle. Bonding can also be an issue if the gauges are expected to last the life of the component. A review of the literature in Chapter 2 suggests that novel sensing technologies such as Uni-Axial Strain Transducers (UAST), piezoelectric sensors or even microelectromechanical systems may provide significantly more reliable strain measurements to fatigue damage models. However, significant development needs to be accomplished before these technologies will be available. Instrumentation that is commonly obtainable and used frequently is more likely to be inexpensive enough and ready for HUMS applications in military ground vehicles.

The models developed in this research utilized sensors that were expected to be sufficiently reliable for use in a HUMS applied to a military ground vehicle. The sensors used can generally be split into two categories. The first are robust sensors that are typically not as susceptible to environmental effects. The models developed in Chapters 3 and 4 utilized speed via Global Positioning Satellite (GPS) sensors and acceleration from accelerometers. Models developed in Chapters 5 and 6 also used acceleration from accelerometers. GPS units are a well developed technology and can provide additional useful data to vehicle operators. Many suppliers exist which makes the technology less expensive. Hardened, durable versions are available and can be easily adapted to a military vehicle. Accelerometers are also common sensors that are used in a variety of testing environments. Accelerometers are relatively durable and reasonable in cost which makes them a good candidate for use in a HUMS.

The second category of sensors used to predict strain that is discussed in this research is instrumentation designed-in during vehicle development. Models developed in Chapter 6 utilized data from sensors already existing on the demonstration vehicle. Most modern military vehicles are arrayed with a variety of sensors to provide feedback to the driver, monitor specific parameters to identify faults, or be used as a diagnostic tool when maintenance is performed. Use of sensors already integrated within the vehicle is an ideal source from which to estimate input parameters to a damage model. These sensors typically have high reliability due to their use in other vehicle subsystems and the cost of integrating them within the HUMS is minimal in comparison with the cost of adding an additional sensor. Improvement in the quality of these sensors may be justified if the improvements provide measurements more suitable for utilization in remaining life prognostics algorithms. Sensors developed and integrated during the design phase of the vehicle can be more cheaply implemented than those added after the design is finalized. These sensors are more robust when they are added during design because the surrounding structure can be manipulated to provide protection from adverse environmental effects. Connections and communication links also have increased durability and survivability when they are added during the design phase.

7.2.2 Strain Indicators

Another issue for sensors in HUMS applications is that the combination of integrated and add-on sensors make a large group of candidates, but the best indicators of strain may not be clearly identifiable. Two methods to identify and select sensors that provide inputs suitable for fatigue damage models were proposed in Chapter 6.

The first method utilized to identify strain indicators was the use of statistics to show a relationship between the critical strain and potential sensors. Two statistics were evaluated based on ability to identify data that provides accurate fatigue predictions for a complexly loaded component on a military wheeled vehicle. Results from the case study in Chapter 6 showed that normalized cross-correlation provides the most accurate fatigue estimates, but calculation of the coefficient of determination of root mean square statistics as an additional means of comparison is recommended for identifying the best overall candidate sensor.

As an alternate method to utilizing statistics to select sensors that indicate strain on a component, sensors can be selected based on those necessary to provide input to a physics-based estimation of the loading on vehicle subsystems. A physics-based estimation may require a large number of sensors, and the subsystem level information required to implement the models may be significant. Results from the case study in Chapter 6 showed that the quality of data provided by sensors is a key contributor to the ability to make accurate damage estimations using physics-based load models.

7.3 Summary and Contributions

In summary, this research was successful in demonstrating that HUMS are a viable technology for tracking fatigue of metal components in military wheeled vehicles. Algorithms specific to predicting damage accumulated were developed that could be reasonably computed real-time as part of an on-board, inexpensive HUMS. A range of models were developed and fidelity of the models was shown to be correlated with the computational complexity. Simplistic models that tracked a large number of components had the least potential for accurate fatigue damage predictions while high fidelity physics-based models had the most potential. Recommendations for the information needed to select the most appropriate model for a component and optimize the effect on vehicle reliability and availability were made. Methods for identifying the set of instrumentation that could reasonably be used as part of a HUMS, and techniques for selecting the instrumentation that provides inputs for metal fatigue damage models were evaluated. Example vehicles and components were selected and results were compared with high fidelity physics of failure models to demonstrate feasibility of the developed algorithms (See Appendix A). Recommendations and reasoning were made for incorporation of HUMS development throughout a military vehicle life cycle.

The processes developed could be easily adapted to other platforms including commercial fleets of vehicles or aircraft. The algorithms and techniques evaluated provide potential for improving reliability and availability, but it should be noted that other methods may be more appropriate depending on the specific vehicle and failure mode. Fixed interval replacement, sparing or component redesign may be more suitable depending on the mode of failure, criticality of component, and HUMS costs.

7.4 Limitations and Future Work

In general significant work remains before there can be widespread application of HUMS and remaining life prognostics on military ground vehicles. The only failure mode investigated in this research was fatigue on metals. Other materials and modes of failure would need to be similarly evaluated to determine if HUMS and remaining life prognostics can be performed for a military wheeled vehicle.

Each of the models developed in this work were based on a single vehicle and operator on courses within a limited geographic area. Vehicle setup and usage can vary significantly and the effects of these changes were not quantified in this analysis.

Changes based on locataion and weather also were not considered. Courses that represent the full spectrum of terrain types likely to be encountered should be evaluated and the variations between operators and vehicles should be analyzed before the proposed HUMS models are universally applied.

From a systems level standpoint, guidelines or methods for evaluating the improvements of reliability and availability due to HUMS technology versus other options are needed. Gains in vehicle reliability and availability need to be weighed against the cost, time to develop and repair time of a system to determine what method is most appropriate. It is unlikely that all the information will be known to optimize the number of components modeled and type of models used, so guidelines or estimating techniques are needed to provide a reasonable balance of resources with needs. New metrics are needed for estimating effects of HUMS on reliability growth models and system evaluations.

Recommendations for selecting sensors to provide reliable inputs to remaining life prognostics models were discussed. However, no sensing technology can guarantee perfect reliability. Methods for error checking are needed to provide warning of sensor failure and prevent premature replacement of the monitored component or missed damage cycles. Techniques and algorithms are needed to deal with signal interruption or contamination. If redundant sensors are used, methods to determine which sensor provides the most accurate data are needed.

Specific to the models developed here, there are also a number of limitations that need to be addressed. A more thorough investigation of the frequency content may indicate the critical aspects of loading and minimize the number of cycles that are necessary to analyze. Relationships between critical frequencies and terrain type, input sensors, or even vehicle speed may improve accuracy of the remaining life prognostics models developed in Chapters 3 through 6 while decreasing the required computational effort.

For the terrain sensing models described in Chapters 3 and 4, limits were developed based on a single vehicle. Variations between vehicles and drivers would need to be quantified and addressed for these algorithms to be applied to a fleet. The models in Chapters 3 and 4 utilized an accelerometer on the sprung mass of the vehicle as the input to terrain identification algorithms. An accelerometer on the unsprung mass may provide more consistent readings between vehicles regardless of condition or payload.

A method to identify components analytically where acceleration and strain have similar waveforms would be useful to determine when models such as the direct strain model in Chapter 5 are applicable. The method proposed required collection of test data to determine if measured acceleration and strain were suitably compatible. Analytical models may help to identify the instrumentation and location necessary to obtain the strain proportional waveforms required by the direct strain models in Chapters 5 and 6.

For the direct strain models discussed in Chapters 5 and 6, a nonlinear scaling method may provide more accurate strain estimates and resulting fatigue damage calculations. Linear scaling was used to maintain a simple relationship between input channels and strain, but a power or exponential function may provide more accurate results with minimal increase in computational effort. The scaling method used in

Chapter 6 for multiaxial strain was based on absolute maximums. The studies on the uniaxial case in Chapter 5 showed that fatigue based scaling provided significantly more accurate damage predictions. A method to implement fatigue based scaling could improve HUMS predictions on a multiaxial case similarly.

The research proposed a methodology for implementing HUMS and remaining life prognostics on military wheeled vehicles. While the algorithms developed are limited to metal fatigue, many of the constraints and requirements should be applicable to a broad range of failure mechanisms. Significant work remains to implement these technologies, but increased reliability and availability of military vehicle systems is a worthy goal.

Appendix A

A baseline physics of failure analysis was performed on the example mechanical component and used to demonstrate that the proposed HUMS algorithms are appropriate and provide suitably accurate fatigue predictions. Figure A.1 illustrates process for high fidelity physics of failure analyses used for mechanically loaded components where metal fatigue has been identified as the root cause of failure. Loading or strain data is collected from dynamics models or live testing at or near the failure location of a component. Finite element analysis is used to map the strain or loads to the strain at the critical location. A critical plane method or rainflow cycle counting is then performed on the resulting strain time histories and the equivalent damage is calculated for each cycle. The fatigue damage accumulation is estimated based on a damage summation method.

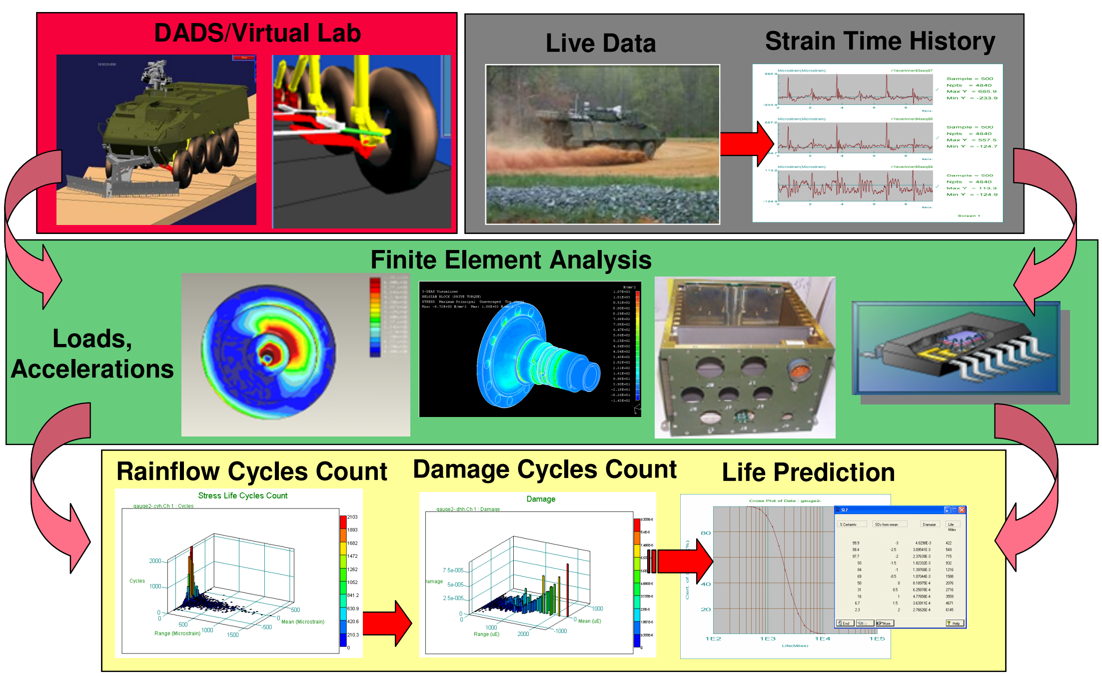

Figure A.1: Physics of Failure process

Appendix B

Normalized cross-correlation and coefficient of determination of RMS were evaluated based on ability to identify data that provide accurate fatigue predictions. To investigate the consistency of indicators between terrain types, results for the training data were separated into primary, secondary and off-road terrains. Results from the normalized cross-correlation, with and without a maximum time shift of 0.5 seconds, are listed in Table B.1 through B.3. Coefficient of determination of RMS results are listed in Table B.4 through B.6. The candidate sensor with maximum values of average normalized cross correlation for the strains attributed to terrain induced loading (Strain 1 and Strain 2) and the drivetrain torque (Strain 3) are labeled in bold font.

Table B.1: Primary normalized cross-correlation with strain

Channel	**Primary Strain 1 Normalized Cross-correlation with, without lag**	**Primary Strain 2 Normalized Cross-correlation with, without lag**	**Primary Strain 3 Normalized Cross-correlation with, without lag**
Battery Voltage	0.02, 0.02	0.05, 0.05	0.04, 0.04
Engine Temperature	0.03, 0.03	0.05, 0.05	0.05, 0.05
Engine Speed	0.02, 0.02	0.05, 0.05	0.04, 0.04
Instant Fuel Economy	0.17, 0.15	0.05, 0.04	0.33, 0.31
Percent Accelerator Pedal Position	0.17, 0.16	0.07, 0.07	0.31, 0.29
Percent Engine Load	0.11, 0.11	0.05, 0.05	0.14, 0.12
Transmission Oil Temperature	0.02, 0.02	0.05, 0.05	0.04, 0.04
Transmission Output Shaft Speed	0.01, 0.01	0.05, 0.05	0.05, 0.05
Fuel Rate	0.02, 0.02	0.05, 0.05	0.04, 0.04
Vehicle Speed	0.08, 0.07	0.05, 0.05	0.03, 0.02
Sprung Accel Front Left Side	0.06, 0.04	0.02, 0.00	0.09, 0.08
Sprung Accel Rear Left Side	0.05, 0.04	0.06, 0.05	0.02, 0.01
Sprung Accel Rear Right Side	0.06, 0.05	0.08, 0.07	0.02, 0.00
HMS Axle 1 Left Side	0.55, 0.55	0.30, 0.30	0.63, 0.60
HMS Axle 1 Right Side	0.13, 0.12	0.47, 0.46	0.35, 0.35
HMS Axle 3 Left Side	**0.66, 0.64**	**0.50, 0.49**	**0.71, 0.70**
HMS Axle 3 Right Side	0.09, 0.07	0.35, 0.34	0.37, 0.37

Table B.2: Secondary normalized cross-correlation with strain

Channel	**Secondary Strain 1 Normalized Cross-correlation with, without lag**	**Secondary Strain 2 Normalized Cross-correlation with, without lag**	**Secondary Strain 3 Normalized Cross-correlation with, without lag**
Battery Voltage	0.01, 0.01	0.00, 0.00	0.00, 0.00
Engine Temperature	0.01, 0.01	0.00, 0.00	0.01, 0.01
Engine Speed	0.01, 0.01	0.02, 0.02	0.02, 0.02
Instant Fuel Economy	0.21, 0.16	0.06, 0.04	**0.44**, 0.40
Percent Accelerator Pedal Position	0.09, 0.07	0.02, 0.01	0.29, 0.26
Percent Engine Load	0.10, 0.10	0.05, 0.04	0.22, 0.21
Transmission Oil Temperature	0.01, 0.01	0.00, 0.00	0.01, 0.01
Transmission Output Shaft Speed	0.01, 0.01	0.01, 0.01	0.11, 0.10
Fuel Rate	0.14, 0.11	0.03, 0.01	0.35, 0.32
Vehicle Speed	0.02, 0.01	0.00, 0.00	0.11, 0.11
Sprung Accel Front Left Side	0.11, 0.01	0.09, 0.02	0.06, 0.01
Sprung Accel Rear Left Side	0.15, 0.14	0.15, 0.13	0.05, 0.01
Sprung Accel Rear Right Side	0.20, 0.18	0.19, 0.17	0.06, 0.03
HMS Axle 1 Left Side	0.23, 0.22	0.20, 0.20	0.33, 0.31
HMS Axle 1 Right Side	0.10, 0.09	0.19, 0.18	0.23, 0.22
HMS Axle 3 Left Side	**0.36, 0.33**	**0.36, 0.34**	0.41**, 0.40**
HMS Axle 3 Right Side	0.20, 0.20	0.31, 0.31	0.16, 0.16

Table B.3: Off road normalized cross-correlation with strain

Channel	Off Road Strain 1 Average Normalized Cross-correlation with, without lag	Off Road Strain 2 Average Normalized Cross-correlation with, without lag	Off Road Strain 3 Average Normalized Cross-correlation with, without lag
Battery Voltage	0.00, 0.00	0.00, 0.00	0.00, 0.00
Engine Temperature	0.00, 0.00	0.00, 0.00	0.00, 0.00
Engine Speed	0.01, 0.01	0.01, 0.01	0.03, 0.03
Instant Fuel Economy	0.13, 0.11	0.04, 0.04	**0.34, 0.29**
Percent Accelerator Pedal Position	0.06, 0.05	0.02, 0.02	0.18, 0.15
Percent Engine Load	0.04, 0.04	0.02, 0.01	0.11, 0.11
Transmission Oil Temperature	0.00, 0.00	0.00, 0.00	0.00, 0.00
Transmission Output Shaft Speed	0.03, 0.03	0.01, 0.01	0.05, 0.04
Fuel Rate	0.08, 0.07	0.02, 0.02	0.23, 0.20
Vehicle Speed	0.03, 0.02	0.01, 0.01	0.07, 0.06
Sprung Accel Front Left Side	0.17, 0.10	0.13, 0.08	0.18, 0.06
Sprung Accel Rear Left Side	0.26, 0.26	0.22, 0.20	0.18, 0.17
Sprung Accel Rear Right Side	0.28, **0.27**	0.23, 0.22	0.22, 0.21
HMS Axle 1 Left Side	**0.29**, 0.27	0.28, 0.26	0.28, 0.22
HMS Axle 1 Right Side	0.27, 0.22	**0.34, 0.30**	0.15, 0.09
HMS Axle 3 Left Side	0.19, 0.17	0.21, 0.19	0.23, 0.21
HMS Axle 3 Right Side	0.21, 0.20	0.28, 0.27	0.09, 0.09

For primary terrain, the height management system sensors provided very accurate input for all three strains. The training course used for primary terrain involved long straight portions followed by tight turns. The only significant powertrain and suspension events would occur near the turns where the HMS was also active. Thus, the measured strains would closely follow the HMS sensor located near the component. The secondary and off road courses are significantly more random and the behavior for both the powertrain and suspension subsystems are more decoupled. Torque applied through the powertrain varies depending on upcoming obstacles which leads to an engine parameter (instant fuel economy) providing the best indication of powertrain induced torque. HMS sensors or sprung acceleration still provide the best indication of suspension loading. Including delay made relatively minor changes to the average cross-correlation values, although allowing for a lag did result in the selection of a different input channel for Strain 3 on the secondary and Strain 1 on the off road course.

Table B.4: Primary coefficient of determination of RMS with RMS strain

Channel	**Primary Strain 1 R^2 RMS**	**Primary Strain 2 R^2 RMS**	**Primary Strain 3 R^2 RMS**
Battery Voltage	0.02	0.01	0.00
Engine Temperature	0.00	0.06	0.02
Engine Speed	0.00	0.01	0.04
Instant Fuel Economy	0.01	0.00	0.11
Percent Accelerator Pedal Position	0.00	0.00	0.00
Percent Engine Load	0.01	0.03	0.01
Transmission Oil Temperature	0.00	0.03	0.01
Transmission Output Shaft Speed	0.10	0.15	0.10
Fuel Rate	0.00	0.00	0.00
Speed	0.09	0.15	0.09
Sprung Accel Front Left Side	0.00	0.00	0.01
Sprung Accel Rear Left Side	0.02	0.03	0.01
Sprung Accel Rear Right Side	0.01	0.00	0.00
HMS Axle 1 Left Side	0.43	0.38	**0.50**
HMS Axle 1 Right Side	0.32	0.39	0.16
HMS Axle 3 Left Side	**0.50**	**0.51**	0.48
HMS Axle 3 Right Side	0.11	0.13	0.04

Table B.5: Secondary coefficient of determination of RMS with RMS strain

Channel	**Secondary Strain 1 R^2 RMS**	**Secondary Strain 2 R^2 RMS**	**Secondary Strain 3 R^2 RMS**
Battery Voltage	0.01	0.00	0.01
Engine Temperature	0.01	0.00	0.09
Engine Speed	0.01	0.01	**0.24**
Instant Fuel Economy	0.03	0.03	0.01
Percent Accelerator Pedal Position	0.00	0.00	0.00
Percent Engine Load	0.07	0.09	0.00
Transmission Oil Temperature	0.04	0.03	0.00
Transmission Output Shaft Speed	0.07	0.03	0.05
Fuel Rate	0.01	0.01	0.00
Speed	0.07	0.03	0.06
Sprung Accel Front Left Side	0.18	0.15	0.01
Sprung Accel Rear Left Side	**0.20**	**0.17**	0.00
Sprung Accel Rear Right Side	0.18	0.17	0.00
HMS Axle 1 Left Side	0.07	0.04	0.01
HMS Axle 1 Right Side	0.03	0.04	0.04
HMS Axle 3 Left Side	0.00	0.00	0.07
HMS Axle 3 Right Side	0.00	0.00	0.05

Table B.6: Off road coefficient of determination of RMS with RMS strain

Channel	**Off Road Strain 1 Average R^2 RMS**	**Off Road Strain 2 Average R^2 RMS**	**Off Road Strain 3 Average R^2 RMS**
Battery Voltage	0.01	0.00	0.02
Engine Temperature	0.02	0.02	0.01
Engine Speed	0.07	0.05	0.01
Instant Fuel Economy	0.04	0.01	0.07
Percent Accelerator Pedal Position	0.03	0.01	0.05
Percent Engine Load	0.15	0.06	0.11
Transmission Oil Temperature	0.04	0.05	0.02
Transmission Output Shaft Speed	0.03	0.03	**0.22**
Fuel Rate	0.05	0.01	0.06
Speed	0.02	0.03	0.19
Sprung Accel Front Left Side	0.18	0.12	0.01
Sprung Accel Rear Left Side	0.22	0.13	0.05
Sprung Accel Rear Right Side	**0.24**	**0.16**	0.08
HMS Axle 1 Left Side	0.00	0.04	0.10
HMS Axle 1 Right Side	0.04	0.05	0.10
HMS Axle 3 Left Side	0.01	0.02	0.13
HMS Axle 3 Right Side	0.02	0.02	0.07

Coefficient of determination of RMS showed very similar results to the normalized cross-correlation. All three strains closely followed HMS sensor data for primary terrain. Sprung mass acceleration showed the best match for suspension loads on secondary and off road terrains and the torque induced by the powertrain was best indicated by engine or transmission data. Care should be taken when selecting course data to train remaining life prognostics algorithms so that specialized driving events do not result in misleading indicators.

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