Alternative Approaches for Health Assessment of Vehicle Subsystems

Kavindu Ranasinghe [1], Rohan Kapoor [1], Alessandro Gardi [1], Roberto Sabatini [2], Vishwanath Wickramanayake [3], David Ludovici [3]

[1] *Cyber Physical and Autonomous Systems Group, Royal Melbourne Institute of Technology, Melbourne, Victoria, 3001, Australia*
[2] *Department of Aerospace Engineering, Khalifa University, Abu Dhabi, United Arab Emirates*
[3] *Land Engineering Agency, Australian Department of Defence, Melbourne, VIC 3006, Australia*

Abstract

The recent drives to increase efficiency in vehicle systems has led to an increased interest in developing vehicle health management systems. The use of artificial intelligence and machine learning algorithms would be vital for these applications to identify trends in vehicle performance and make inferences of the current and future state of health of safety-critical subsystems. This paper presents a study done using the outputs from diagnostic and prognostic models based on data gathered by Health and Usage Monitoring System sensors on-board Armoured Personnel Carriers. Based on the requirements and the data being processed for insights, the outputs from these models are subject to different reasoning techniques, inference tools and algorithms. This includes a sensor signal validation and anomaly detection tool in which a trained probabilistic neural network is used to identify off-nominal behaviour in sensor data, thus aiding in the health assessments and integrity checks of sensors. Additionally, Kalman filtering is employed to utilize the dynamic equations that govern the operation of the powertrain. An Extended Kalman Filter (EKF) algorithm is developed to determine instances where there are large discrepancies between the measured and estimated value, indicating a possible fault.

Keywords: Sensor Networks, Health and Usage Monitoring Systems (HUMS), Vehicle Health Management, Artificial Intelligence

Introduction

The concept of Health And Usage Monitoring Systems (HUMS) was initially introduced by the National Aeronautics Space Administration (NASA) in 1992, as a technology to collect data, diagnose, predict and mitigate faults, and support the operational decisions and post-operational maintenance activities of space vehicles [1]. Current HUMS technologies encompass many vehicle industries such as aircraft, ships and automobiles, particularly in the defence sector [2, 3]. These systems help reduce the cost of maintenance, repair and overhaul (MRO) of individual and fleet assets. However, further development of this technology in the future would be essential for the application of safe and reliable autonomous vehicles as they would require the capacity to predict system faults prior to a catastrophic event.

Typically, HUMS comprises a suite of sensors which capture and store large amounts of status data at vehicle, system and component levels [4]. This provides an opportunity to leverage the data to develop intelligent vehicle health management systems with the intention of increasing the levels of efficiency and effectiveness of individual assets and vehicle fleets, which can translate into tangible mission, maintenance and support benefits. The overall benefits expected from an opportune exploitation of this technology are improved availability, safety and reliability of vehicles and components as well as the minimization of operational, maintenance and life-cycle costs also in relation to a reduction in the redundancy levels [5, 6].

In this study, several AI based diagnostic and prognostic tools were developed to analyse data gathered by HUMS sensors onboard an Armoured Personnel Carrier (APC). The implementation of these techniques in vehicle health management systems to make fault predictions has a strong potential to enhance safety, reliability and efficiency across many different applications, particularly in the field of autonomous vehicle applications.

State-Of-Health Analysis Using HUMS

Figure 1 provides a basic overview of the state-of-health monitoring and management process using HUMS data. The data is gathered from a number of sensors across the vehicle. These sensors range from conventional embedded sensors to more advanced smart and wireless sensors.

The data utilized for this study was taken from a fleet of 149 APCs fitted with standard HUMS equipment, including over 50 data channels from on-board sensors linked via a Controller Area Network (CAN bus) in each APC as shown in Figure 2. A selection of these sensor variables that were used in this study are presented in Table 1. A vehicle data logger is used to capture and store data throughout all mission profiles carried out by each APC. These profiles include both periods of vehicle activity and idle periods during normal operation. At the end of each session, the gathered raw vehicle data is transferred via WiFi or 3/4G automatically to a data storage facility, processed and can then be used for analysis.

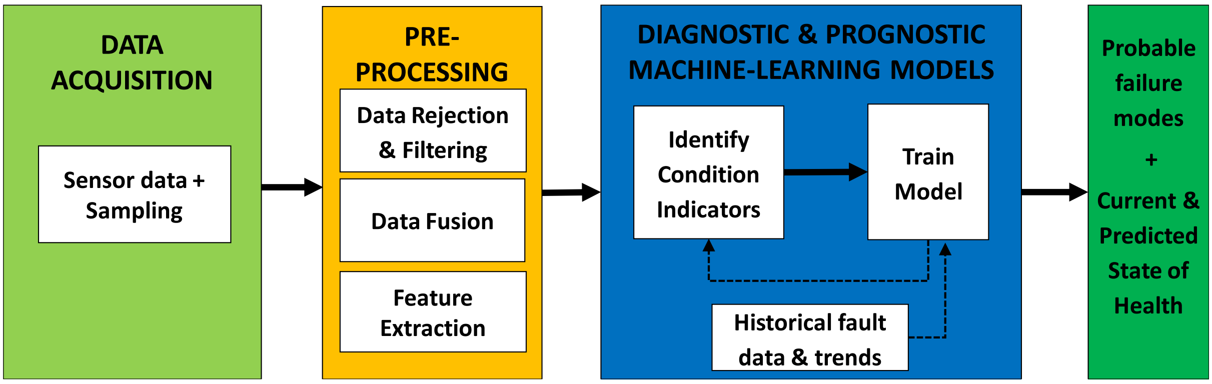

Figure 1: HUMS data workflow diagram

Raw measurement data collected from all sensors is filtered, fused and analysed. Data rejection and filtration is required in this step to remove outliers and noise, to get a realistic picture of normal behaviour. Instead of feeding sensor data directly into machine learning models, it is necessary to extract features from the sensor data. These features capture higher-level information in the sensor data, for example, moving averages or frequency content.

In the next step, the parameters acting as condition indicators for faults are identified and monitored to detect, identify and characterise faults by studying anomalies and trends. Diagnostic processes allow the rapid determination of specific components/systems that need to be replaced during maintenance and can also contribute to a better understanding on the factors causing any premature failure. Prognostic processes, on the other hand, enable the prediction of the residual life of components/systems and the most likely failure mode by analysing trends in historical observations and implementing model-based estimations [7].

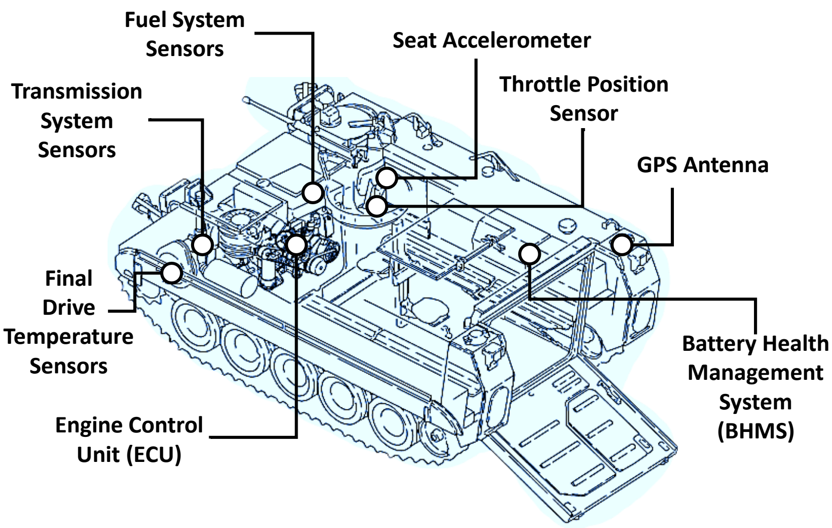

Figure 2: APC fitted with HUMS Sensor Suite

Table 1: List of sensor variables

Sensor	Units	Additional Notes
Throttle Position	%	Ratio of actual position of accelerator pedal to maximum position
Driver Demand Engine Torque	%	Instantaneous engine torque demanded by driver. Calculated by Engine Control Unit (ECU)
Actual Percent Engine Torque	%	Output torque of engine calculated by ECU
Engine RPM	rev/m	Operating speed of engine calculated by ECU
GPS Altitude	m	Height above sea level
GPS Latitude	degrees	Latitude co-ordinate of vehicle
GPS Longitude	degrees	Longitudinal co-ordinate of vehicle
GPS Speed	km/hr	Derived from GPS data
GPS Time	N/A	Measured by GPS
Ambient Air Temperature	°C	-
Engine Oil Viscosity	cP	Measured by an oil condition sensor.
Engine Oil Temperature	°C	Measured by engine ECU and data relayed to the VCU.
Engine Oil Pressure	kPa	Sensor provides signal source variations proportional to engine oil pressure (gauge pressure)
Total Engine Hours (ECU + HUMS)	hrs	Incremented when the condition (Engine RPM>=200 for 0.1 sec) is satisfied

AI-Based Diagnostic and Prognostic Tools

Sensor Data Pre-processing and Anomaly Detection Using a Probabilistic Neural Network

One of the most significant areas to consider when implementing an Integrated Vehicle Health Management (IVHM) system is to ensure the reliability of all measured parameters. The diagnostic and prognostic algorithms must be able to distinguish between anomalies that occur with the systems and those that occur due to the result of normal transients or faulty sensors. In particular, a prime cause of erroneous sensor data is damaged or defective sensor cable connectors. Therefore, a comprehensive signal validation and anomaly detection module is needed to act as a front-end to validate and call out health status anomalies from the sensed signals prior to further analysis [17].

One of the AI techniques that can be applied to address this issue is based on a probabilistic neural network (PNN) modelling technique that can use normal system operating data to detect off-nominal behaviour. The PNN is trained to predict a signal, with inputs that are correlated to it in some manner over an appropriate dynamic range.

As an example, the variation of engine oil viscosity with temperature was examined. Figure 3a shows the variation of these two parameters for a given operating session. It is evident from the graph that there is a clear relationship between engine oil viscosity and engine oil temperature. This relationship can be modelled by various equations including Ubbelohde-Walther equation, Vogel-Cameron equation and the Wright model [18]. This is the basis for the estimate of KV100 (Kinematic Viscosity at 100°C) which is required as an indicator of engine oil degradation. However, there are many anomalous points which need to be discarded from the sensor data, including some readings with a temperature of 273K (0°C) which likely correspond to instances where the sensor is still adjusting to the environment. A PNN model was constructed and trained to recognize data points that correspond to expected values along the viscosity-temperature curve, to the readings of 0°C and to other anomalies. The results of the model are plotted in Figure 3b.

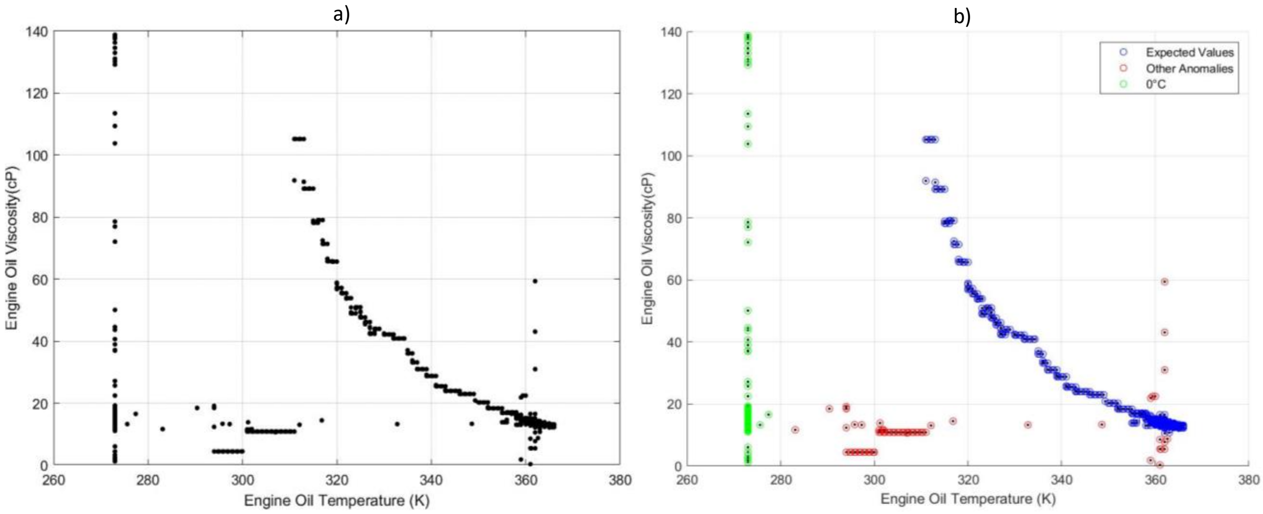

Figure 3: Engine Oil Viscosity vs Engine Oil Temperature a) before PNN data classification b) after PNN data classification

In this case, there is value in distinguishing between the type of anomalies that occur along with their associated frequency of occurrence and magnitude. An increase in 0°C readings could mean that the sensor is taking too long to calibrate to its environment, whereas an increase in the number and/or magnitude of other anomalies could mean that the signal from the sensor is corrupted in some way. The health assessment based on this information can be performed by a decision level fusion output that determines whether a particular sensor or health feature has anomalies or is damaged and therefore unreliable.

Powertrain Fault Detection Using an Extended Kalman Filter

The information that can be inferred from the HUMS data regarding the motion of the vehicle and the forces and moments acting on it can be leveraged in a model-based reasoning approach to detect faults in the powertrain. In this study, this was constructed in the form of an Extended Kalman Filter (EKF).

The first step involved defining the dynamics equation that describes the function of the physical model. For this we consider the relationship between the torque at the wheel (T_w) and the angular acceleration of the wheel ($\dot{\omega}$) given by:

$$\dot{\omega} = \frac{(T_w - c\omega)}{J_w} \tag{1}$$

where J_w , ω and c are the inertia, angular velocity and damping coefficient of the wheel respectively.

T_w can be derived from the measured engine output torque T_{ENG} from the HUMS data using the following equation, which represents the behaviour of the drivetrain.

$$T_{ENG} = \frac{T_W}{i_g i_f \eta_t} \tag{2}$$

where i_g is the gearbox ratio, i_f is the final drive ratio and η_t is the transmission efficiency. To estimate the damping coefficient, we introduce an auxiliary state for the damping coefficient and set its derivative to zero.

$$\dot{c} = 0 \tag{3}$$

The state vector x and the prediction step to calculate the next state vector is given by:

$$x = \begin{bmatrix} \omega \\ c \end{bmatrix} \tag{4}$$

On the other hand, the measurement step uses the inputs of ω and $\dot{\omega}$ taken from the sensor data. This step is defined by the following equation:

$$y = \begin{bmatrix} \omega \\ (T_w - c\omega)/J_w \end{bmatrix} = \begin{bmatrix} \omega \\ \dot{\omega} \end{bmatrix} \tag{4}$$

Physical systems are usually represented as continuous-time models while discrete-time measurements are required to be taken for state estimation via the EKF algorithm. The discrete time model equations for the system as well as the model are given by the following equations respectively:

$$\begin{aligned} x_{n+1} &= \begin{bmatrix} \omega_{n+1} \\ c_{n+1} \end{bmatrix} = \begin{bmatrix} \omega_n + \dot{\omega}\Delta T \\ c_n + \dot{c}\Delta T \end{bmatrix} \\ &= \begin{bmatrix} \omega_n + \left(T_{w_n} - c_n\omega_n\right)\Delta T/J_w \\ c_n \end{bmatrix} \end{aligned} \tag{5}$$

$$y_n = \begin{bmatrix} \omega_n \\ \dot{\omega}_n \end{bmatrix} \tag{6}$$

The next step is to define the state (process) noise disturbances q and the measurement noise disturbances r. These noise terms are additive and modify the discrete time model equations:

$$x_{n+1} = \begin{bmatrix} \omega_n + \left(T_{w_n} - c_n\omega_n\right)\Delta T/J_w \\ c_n \end{bmatrix} + q \tag{7}$$

$$y_n = \begin{bmatrix} \omega_n \\ \dot{\omega}_n \end{bmatrix} + r \tag{8}$$

The process and measurement noise have zero mean and covariances Q and R. In the EKF implementation, the friction state has a high process noise disturbance which reflects the fact that the friction coefficient is expected to vary during normal operation. The aim is to track this variation. The covariance of the measurement noise was calculated based on the accuracy of the readings of the angular velocity which are derived from the vehicle speed, which in turn is derived from GPS measurements.

The function f can be used to compute the predicted state from the previous estimate and similarly the function h can be used to compute the predicted measurement from the predicted state. However, f and h cannot be applied to the covariance directly. Instead, a matrix of partial derivatives (the Jacobian) is computed. The Jacobian of the state function and the measurement function are evaluated at each time step and are defined by defined by the following equations:

$$\frac{\partial f}{\partial x} = \begin{bmatrix} 1 - \Delta T c_n/J_w & \Delta T \omega_n/J_w \\ 0 & 1 \end{bmatrix} \tag{9}$$

$$\frac{\partial h}{\partial x} = \begin{bmatrix} 1 & 0 \\ -c_n/J_w & -\omega_n/J_w \end{bmatrix} \tag{10}$$

The EKF algorithm requires an initial state vector x_0 as a starting point from which the filter eventually converges to the solution.

The idea behind setting up a model this way is to monitor certain parameters during the operating session of the vehicle. Any instance where the estimated value of the monitored variables greatly differs from its measured value could be indicative of faulty behaviour. The EKF algorithm enable the estimation of the states, and in this scenario, we are particularly interested in the damping coefficient state of the wheel. Figure 4a shows a sample of data input to the EKF algorithm, whereas Figure 4b shows the output.

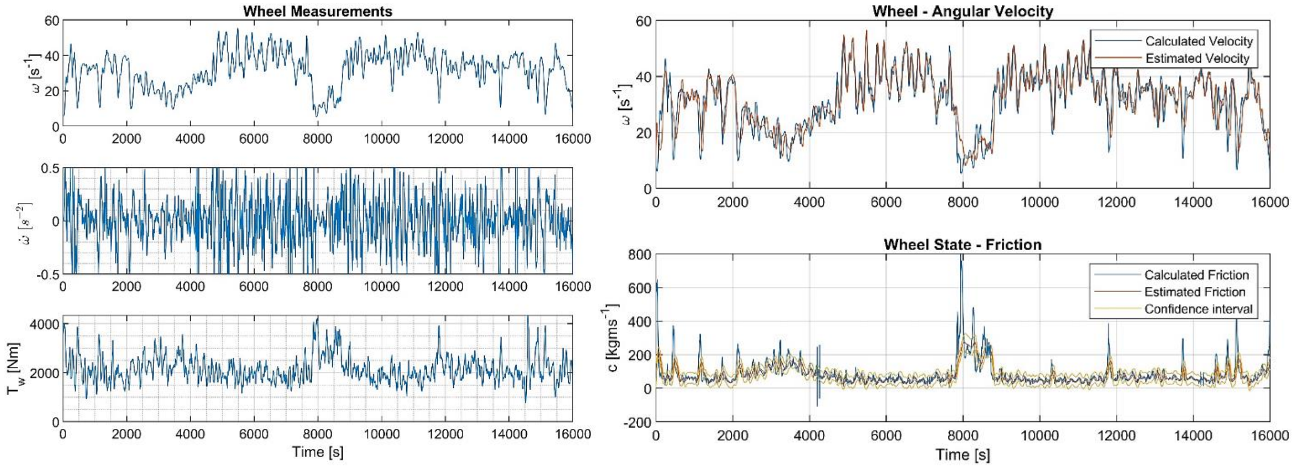

Figure 4: a) Wheel measurements for a given APC b) EKF state estimation

The estimated friction state is shown with confidence intervals corresponding to 3 standard deviations. The calculated friction is that obtained from the system dynamic model. It can be observed that the friction coefficient varies significantly throughout the regular operation of the vehicle. The underlying hypothesis of this methodology is that a large discrepancy between the friction coefficient calculated by the dynamics model and that obtained from the EKF estimation implies the possibility of a fault in the drivetrain. As seen in Figure 4b, there are several occasions where the calculated friction goes beyond the 3-sigma confidence interval of the estimation friction, and this corresponds to the instances with a large error in the estimated angular velocity. In physical terms, this means that there is a mismatch between the theoretical torque being delivered from the engine to the wheel via the drivetrain and the angular velocity with which the wheel is spinning.

Conclusions

This study establishes AI based diagnostic and prognostic tools that utilize HUMS data to provide outputs that can be used to infer the state of health of subsystems of an APC. These tools included a PNN algorithm that can be used to classify sensor data inputs and thereby aid in sensor signal integrity checks. This functionality would particularly be useful when implemented in real-time in autonomous vehicle applications, where operational decisions are made solely based on information gathered by sensors. Another tool that was developed used an EKF algorithm for fault detection of the powertrain which involved monitoring the friction coefficient at the wheel to determine instances where there are large discrepancies between the measured and estimated value. The implementation of these techniques in vehicle health management systems to make fault predictions has a strong potential to enhance safety, reliability and efficiency across many different industries.

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