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REAL-TIME MODEL- AND HARMONICS BASED ACTUATOR HEALTH MONITORING

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Abstract
A Health Monitoring (HM) method, optimized for low computational power real–time computers, is presented for the detection of faults in an Electro Mechanical Actuator (EMA). The method is based on 5 steps: 1. Pre-processing of the sensor data using Kalman filtering, 2. Generating residuals, 3. Selection of the usable data for detection, 4. Harmonic analysis to identify the faults and increase the sensitivity and 5. Decision making to classify the faults. The method is tested on simulation data.

INTRODUCTION

For the monitoring of the health of an actuator multiple approaches can be identified: Methods that use external sensors like vibration sensors (e.g. Ismail, Sawalhi and Pham [1]), methods that use an indirect detection approach e.g. by identifying the oil quality (e.g. Márton and van der Linden [2]) and direct methods that rely only on the sensors that are used for the actuator control. This last method has the advantage that no extra sensors are needed, thereby allowing the failure rate of an EMA to be kept low.

Health monitoring with the on-board sensors of an EMA and thus without specialized sensors can be well compared with looking for a needle in a haystack: The sensors deliver huge amounts of data, but only by a very close analysis is it possible to find the incipient fault that is being searched. The main goal therefore of these HM algorithms is to effectively use this large amount of sensor data and condense it to a single response to the question: Is the actuator healthy or not?

During this data reduction, the large sensor data amounts are used to increase the signal to noise ratio of the measurements and thereby deliver an early and robust answer. The authors propose a patented [3] method for actuator monitoring that is divided in multiple steps:

1. **Filtering:** Kalman filtering uses all on-board sensors at the same time for the filtering. The Kalman filter includes the different statistical noise properties of the sensors and also the knowledge of the dynamic behaviour of the system.
2. **Generating residual signals:** Using the Kalman filtered signals, a residual can be generated. For different incipient faults, different residuals have proven to be the best indicators of the damage. However, a very good indicator has proven to be the difference between the motor resolver and the LVDT measuring the ram position scaled with the total gearing ratio.
3. **Detection Activation:** Based on the speed and further inputs, the detection algorithms are enabled. By including only the data from a moving actuator, noisy data can be avoided.
4. **Harmonic analysis of the residual signal:** Using a harmonic analysis, the residual signals are further processed. A frequency or position based approach can be used, depending on the application. By looking at the fault harmonics this allows for a further increase in the signal to noise ratio.
5. **Decision making to classify the faults:** The amplitudes of the harmonics are classified based on different actuator properties: e.g. actuator temperature or motor speed. These amplitudes are compared to reference amplitudes. Based on this comparison a warning can be issued.

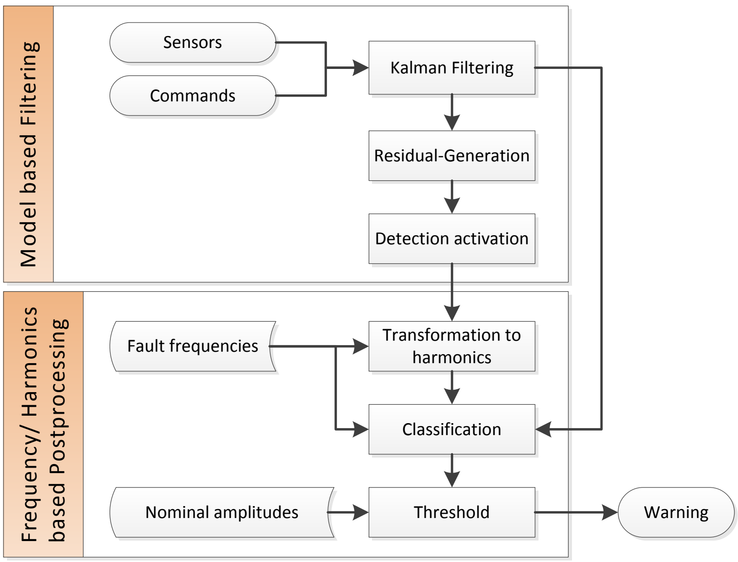

Figure 1. Structure model- and harmonics based health monitoring.

A flowchart of how the detection algorithm is set up is given in Figure 1. Each step of this method will be further highlighted in the next sections. The paper will be concluded with remarks on the difficulties of the HM of EMAs and proposed solutions.

1 MODEL BASED FILTERING

To filter the sensor data, a linear Kalman filter [4] has been developed. Such an algorithm has proven to be a good compromise between filter complexity and performance. For the design of Kalman filters, commercial tools like Matlab are available. The filter includes system knowledge to design a filter that gives an optimal estimate of the system state assuming all noise to be Gaussian noise.

1.1 Linearization of the system model

The system model is modified to have outputs for all sensor signals. Furthermore, artificial extra inputs have been created to include system noise in the design of the Kalman Filter.
The available system model of the actuator in Simulink was linearized. To achieve a good linearized model, a combination of model simplification by hand and linearization in Simulink has been applied. A system with 5 inputs and 6 outputs has been generated this way.

To reduce the computational efforts of the Kalman filter that will be described in the next section, the system is reduced from 9 to 6 states. To achieve this, the system is scaled using the expected input values and the states are balanced to minimize numerical problems. Afterwards an order reduction from 9 to 6 states is applied. By studying the frequency responses of the system, the validity of the system could be confirmed.

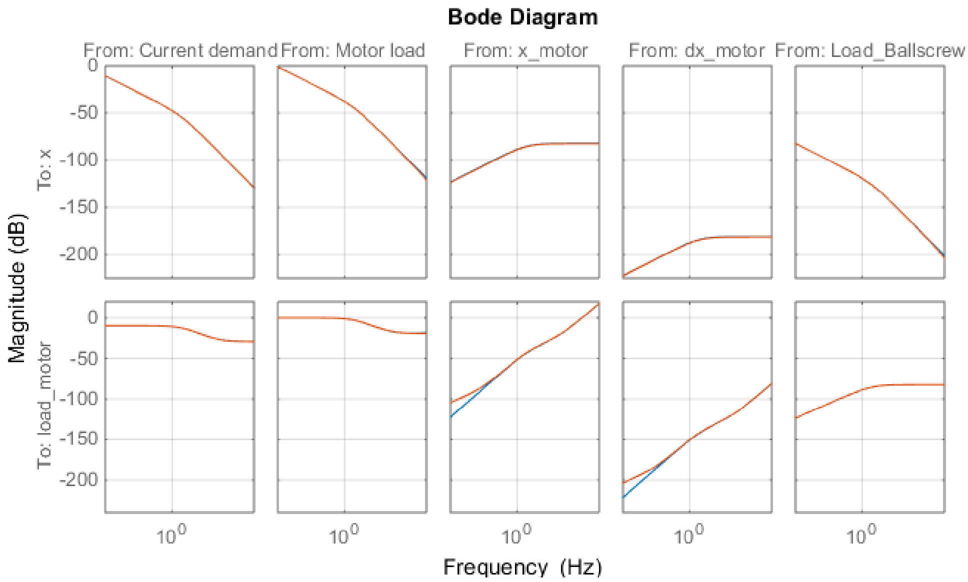

Figure 2. Excerpt of the bode plots of the system (red) and the reduced system (blue)

1.2 Kalman Filter synthesis

Using the linearized model, a Kalman filter is generated. Here, the noise properties of the sensors are considered for the layout of the Kalman filter (see Table 1). All system sensors are identified as sensors. The inputs are divided into “Knowns” for known system inputs and “Process” for unknown noise inputs. Using the Matlab “Control System” Toolbox a Kalman Filter is synthetized in continuous time to filter the sensor data.

Since the HM algorithms will be run on a discrete computer, the Kalman Filter is subsequently transformed into a discrete system.

Table 1. System properties for Kalman Filter generation. The noise levels are normalized to the first entry. The entries marked as SENSOR have been used as sensor input to the Kalman filter and the entries marked with PROCESS as process noise inputs to the Kalman filter synthesis.

Outputs	**ID**	**Normalized Noise Level**
Ram position	SENSOR	1 mm
Ram speed	SENSOR	1 m/s
Motor current	SENSOR	2 A
Motor position	SENSOR	6e-3 rad
Motor velocity	SENSOR	10 rad/s
Motor load	-	-

Inputs	**ID**	**Normalized Noise Level**
Current demand	KNOWN	-
Motor load	PROCESS	1 N
Motor position	PROCESS	0.01 rad
Motor speed	PROCESS	1 m/s
Actuator load	KNOWN	-

2 RESIDUAL GENERATION AND HARMONIC ANALYSIS

The Kalman filter can be used to filter the noisy sensor signals and afterwards a residual is generated by employing model based redundancies. Then for robust detection of the faults, the signal to noise ratio is further increased using signal based methods.

2.1 Residual Generation

A test campaign with thorough testing of an EMA at room and elevated temperature (+70°C) and with different damages on the gear wheels has been carried out in a previous study [5]. By analysing the results from this study, it has been found that for gear faults, two residuals have proven very robust for different temperatures, speeds and loads:

1. The difference between the estimated motor position and estimated ram position times the ratio
2. The difference between the estimated motor speed and estimated ram speed times the ratio

These residuals can be seen as an measurement of what is happening inside the actuator. In an ideal case, this residuum should always be zero. However, when damage occurs, the elasticity, actuator play and transmission ratio can change momentarily. This leads to high frequent changes of the residual when damaged elements are in contact. Examples of such damage are missing teeth or a deformed tooth. Local elasticity changes have been measured in a dedicated test rig [6], but have not been further assessed for health monitoring approaches yet.

2.2 Periodic analysis

To further increase the signal to noise ratio of the residual, a harmonic analysis is carried out. A FFT analysis for constant speed testing has been used in the last projects, which has proven to work well for constant speeds. This method is mainly suitable for pre-flight testing, as the actuator is run at a constant speed.

However, as mentioned before, typical aircraft actuators do not run at a constant speed. Therefore a method has been developed to detect the harmonics in the signal using the current rotational velocity of the motor. A recursive algorithm as presented by Morelli [7] and used for actuator fault detection by Ossmann [8] is further optimized for the use in health monitoring systems for EMAs.

This algorithm has been adapted to detect the harmonics of a signal (vibrations/position) instead of the frequency of the signal (vibrations/sec). This guarantees independence from the actuator speed. The developed recursive harmonic detector yields for faults of constant amplitude a constant result instead of an increasing signal. Furthermore, the harmonic detector uses a built in first order low-pass filter.

Care has been taken that the algorithm can run on real time hardware without saving large quantities of data. The main calculations rely on two memory blocks, an exponential function, several multiplications and an addition.

2.3 Results

To showcase the method, a simulation of an EMA with a damaged gear on the first stage is carried out. The actuator is driven with a varying speed while at the same time the actuator load is varied (see Figure 3). The amplitudes of the harmonic analysis are thereby plotted in Figure 4. As can be seen in this figure, the amplitude of the harmonics belonging to the first gear stage is much higher than the other 2 amplitudes. This clearly identifies the first stage as damaged.

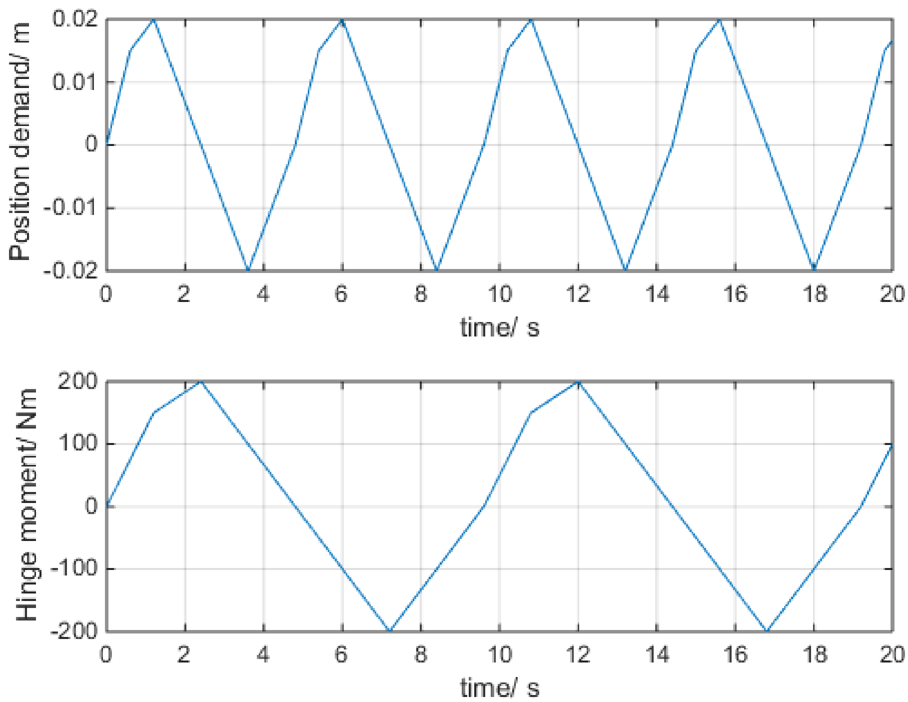

Figure 3. Speed and load of the actuator during the detection.

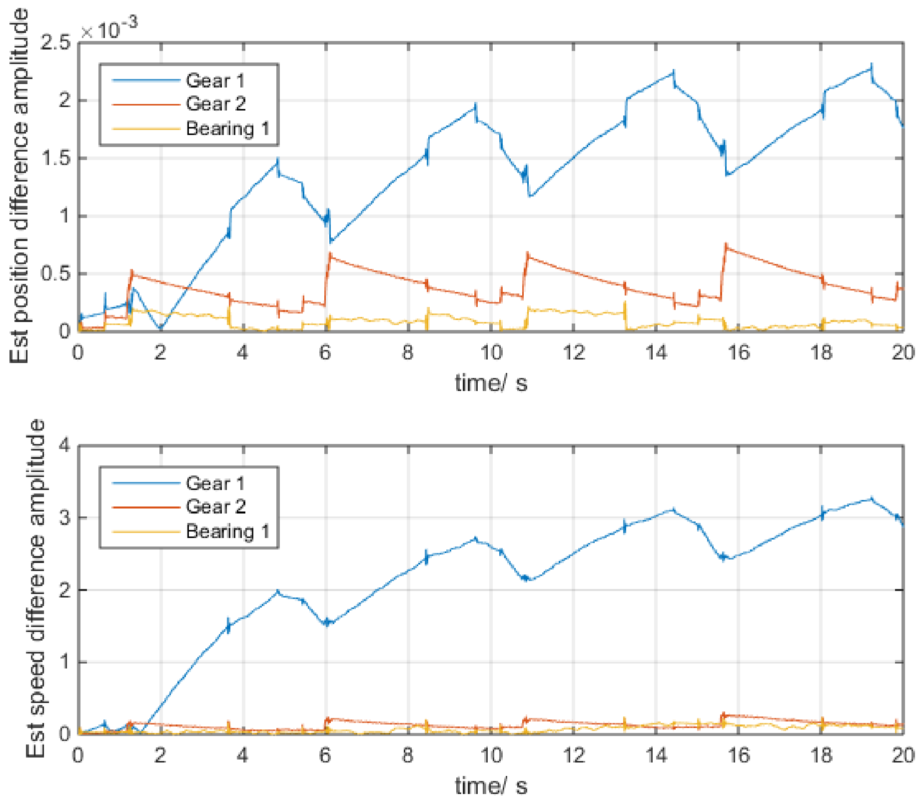

Figure 4. Simulation results of a harmonic analysis of a gear with a fault on the first stage.

3 FAULT CLASSIFICATION AND DECISION MAKING

The amplitude of the residuum spectrum is dependent on the speed, temperature and the loading condition as can be seen in Figure 5. This data is gathered from measurements on an EMA at room and elevated temperature (+70°C) under different loading conditions and speeds. Using Figure 5, the measurements that have a similar fault response can be identified and identified as "detection classes".

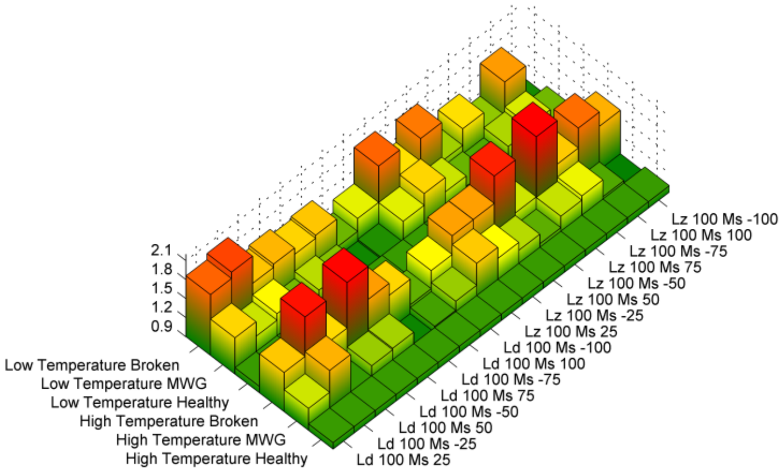

Figure 5. Detectability of the gear faults using only available sensors on the actuator. A higher number indicates a better detectability. The loading condition marked with Ld stand for a compressive load, Lz for tension loads on the actuator. The measurements marked with MWG are the results of the measurements with a plastic deformation of one tooth. Low temperature denotes room temperature and high temperature an elevated temperature (+70°C).

Multiple harmonic filters can be set up, one for each detection class. By enabling the storage of each filter only when the signal is in the right detection class, a computationally effective calculation of detection amplitude for each class can be achieved.

By comparing the detection amplitudes of the classes to known healthy amplitudes, warnings can be given when a threshold is exceeded.

4 CONCLUSION AND DISCUSSION

The methods presented in this paper are optimized for low computational performance hardware. All methods are implemented recursively to reduce data logging and avoid spikes in the computational performance. Although not presented in this paper, the sensor noise rejection of the proposed methods has proved to be good.

While implementing the proposed method, it has become clear that pre-filtering the sensor data before the Kalman filter can lead to better results. It is suspected that this can be caused by the bandwidth limitation of the Kalman filter in a discrete time.

The proposed algorithms are tuned to a single operational point and a set of faults. Using a multi-objective optimisation approach as used by Joos [9] has proven to be valuable for finding the optimal parameters for the filters. Such an optimisation should include multiple optimisation cases (in this cases multiple faults) and multiple objectives (maximisation of the amplitudes due to the faults to be detected, while minimizing the amplitudes of the faults that are to be decoupled).

To cover the different plant responses for different operational regions, multiple Kalman filters and multiple harmonic analysers can be used with individual tuning for each operational point. This is expected to be especially interesting when the faults have a very different base frequency. This is for example the case when comparing a motor-bearing fault to a thrust-bearing fault due to the high gear ratio.

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