Denoising Jet Engine Gas Path Measurements Using Nonlinear Filters

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***Abstract*— A simple but powerful and practical approach using median and rational filters is proposed for removing noise and outliers from gas path sensor measurements which can contain effects of long term deterioration and sudden abrupt faults. Typical gas path measurements used for health monitoring are exhaust gas temperature, low and high rotor speed, fuel flow rate, and pressure and temperature measurements inside the engine. Traditionally, linear filters such as the moving average have been used to smooth time series of gas path measurements before performing fault detection and isolation functions using Kalman filters, neural networks or fuzzy logic. However, linear filters can smooth out sharp trend shifts in the signal and are also not good at removing outliers. Since most fault detection and isolation algorithms are optimized for Gaussian noise, they can show performance degradation when outliers are present. In this study, numerical results with simulated data for engine deterioration and abrupt fault show that the nonlinear rational filter with median preprocessor are useful for gas turbine health monitoring applications resulting in noise reduction of 73-96 percent while preserving signal features and removing outliers.**

***Index Terms*—Gas turbines, signal processing, fault diagnosis.**

I. INTRODUCTION

Health monitoring applications typically involve detection and isolation of a system fault based on a comparison between a "good" baseline system and a "damaged" system. Many diagnostic systems are designed based on mathematical models for the "good" and "bad" systems using methods that fall under the broad class of model based diagnostics [1]. A health signal can be interpreted as a measurement delta between the damaged measurement $z^{(d)}$ and undamaged measurement $z^{(u)}$ and written as: $\Delta = z^{(d)} - z^{(u)}$. Under ideal conditions, when a system has no fault, Δ=0. When a fault occurs, Δ assumes a nonzero value whose magnitude depends of the size and location of the fault. In this idealized system, the nonzero value of the measurement deviation, along with other measurement deviations, can be used to detect and isolate the fault.

Studies of gas turbine data have shown two main features of the health signal Δ: (1) most major problems in the engine are caused by a "single fault" which is preceded by a sharp trend shift [2] and (2) long term deterioration in the engine causes a low order polynomial variation in the measurements with time, with a linear polynomial being a very good approximation [3]. However, noise and outliers are present in the gas turbine health signals. Therefore, processing of health signals is often done before using fault isolation methods using linear filters [4]. However, linear filters smooth out the sharp edges in the signal that contain important information about the fault initiation time as well as repair events and could be used for fault isolation applications. Furthermore, linear filters are not good at removing outliers in the data.

For commercial aircraft engines, only few data points are received for each flight. Therefore, it is important to keep the forward data point requirement to a minimum. In this paper, we explore filters with a low time delay for gas turbine applications.

II. GAS TURBINE DIAGNOSTICS

Figure 1 shows a schematic of a turbofan engine which has five modules: fan, low pressure compressor (LPC), high pressure compressor (HPC), low pressure turbine (LPT) and high pressure turbine (HPT). Faults in the gas turbine engine cause efficiency deterioration for the engine modules. The engine state is monitored using at least the four basic sensors: exhaust gas temperature (EGT), fuel flow (WF), low rotor speed (N1) and high rotor speed (N2). The measurements which are taken at altitude at a given temperature are then converted to standard day sea level conditions and then the baseline measurement of an undamaged engine at the same condition (usually from a thermodynamics based performance model) subtracted from the measurements to yield the measurement deltas ΔEGT, ΔWF, ΔN1 and ΔN2. The measurement deltas are then used for estimating the engine state.

Figure 2 shows a schematic of the gas turbine diagnostic process which used the engine measurement deltas to detect and isolate faults and then suggest prognostic action based on

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non destructive testing, boroscope and manual inspections of the fault module. It is clear that if the fault module is correctly identified, the cost of maintenance of the airline comes down.

III. Test signals

The gas path signals can be modeled using (1) step and (2) ramp edges. Consider the time series for 25 points shown in the ideal step signal in Figure 3. This step signal simulates an abrupt fault. The onset of the fault(s) is at discrete time k=12. The noisy signal can be expressed as

$$\Delta = \Delta^0 + \alpha\ \varepsilon + \theta \tag{1}$$

where Δ^0 is the pure signal, ε and θ are added Gaussian noise and outliers, respectively, and α is a parameter that allows control of the level of noise in the noisy health signal Δ. Figure 3 shows the ideal step signal along with a noisy test signal with α=0.2. The outlier signal contains five points represented by θ=-1 at k=7, θ=0.75 at k=10, θ=-0.75 at k=14, θ=1 at k=18, and θ=-1.5 at k=22. These outliers are placed in an arbitrary way along the time series and do not follow any noise model. Lu [5] calls these "wild points" which tend to occur in gas path sensor measurements. Figure 4 shows the ideal and noisy test signal for a ramp edge simulating engine deterioration. The outliers are placed at the same location as for the step signal.

Table 1 shows the fingerprint chart for a large commercial engine similar to the United Technologies PW4000-94" engine in cruise condition with engine pressure ratio of 1.29 [4]. The fingerprints are fault signatures of the engine at a given steady flight condition and relate the faults in a given module to changes in the gas path measurements. For the fingerprints shown in Table 1, the measurement uncertainties for ΔEGT, ΔWF, $\Delta N2$ and $\Delta N1$ are 4.23 C, 0.50%, 0.17% and 0.25%, respectively [4]. These numbers were obtained by a study of airline data. Using these numbers for the four measurements, the signal to noise ratios are obtained by dividing the fingerprints in Table 1 with the corresponding measurement uncertainty. These results are shown in Table 2 where it can be seen that the signal to noise ratios range from a low of 0.56 to a high of 7.84. Since the ideal test signals in Figure 3 and 4 have a maximum value of one, a noise level of 0.10 leads to a signal to noise ratio of 10 and a noise level of 0.4 leads to a signal to noise ratio of 2.5. Also note that the ideal signals vary from zero in the initial stages to values between 0 and 1 for the ramp edge in Figure 4. Therefore, a wide range of signal to noise ratio are addressed using the variation in α from 0.1 to 0.4. Results shown later in the paper will vary the noise level from 0.10 to 0.4 to allow for evaluation of the filter over a broad range of noise levels likely to occur in gas turbine applications. Note that actual fault data for gas turbines is very difficult to obtain and the use of simulated data allows the evaluation of the filter performance as the ideal signal is known. Furthermore, the types of signals used here have been used in the literature by Lu et al [5] to evaluate a filtering approach based on auto-associative neural networks.

The mean square error (MSE) also provides information about the filter accuracy and is defined as

$$MSE = \sum_{i=1}^{N} \frac{\left(\Delta - \Delta^0\right)^2}{N} \tag{2}$$

where N is the number of samples, Δ is the noisy or filtered signal value and Δ^0 is the ideal or pure signal value. The noise reduction is defined as

$$\Theta^{(MSE)} = 100\,\frac{MSE^{(noisy)} - MSE^{(filtered)}}{MSE^{(noisy)}} \tag{3}$$

IV. background on filtering

The filters used in this study are the rational filter and the median filter.

Rational Filter. The working of rational filter is based upon a non-linear operator, which is able to attenuate the Gaussian noise in a signal, while preserving the edge to a good extent [6]. It is described by a rational function, which is the ratio of two polynomials.

$$\hat{\Delta}_k = \frac{\Delta_{k-1} + \Delta_{k+1} + \Delta_k\left[\kappa\left(\Delta_{k-1} - \Delta_{k+1}\right)^2 + \frac{1}{w} - 2\right]}{\kappa\left(\Delta_{k-1} - \Delta_{k+1}\right)^2 + \frac{1}{w}} \tag{4}$$

Here $\hat{\Delta}_k$ is the filtered signal value at discrete time k. The values of data at k-1, k and kth time are Δ_{k-1}, Δ_k and Δ_{k+1} and these points are the backward predictor, current value and forward predictor, respectively. The parameters κ and w takes positive values and are used to control the filter. The rational filter differs from the linear FIR filter mainly for the scaling which is introduced on the Δ_{k-1} and Δ_{k+1} terms. Such terms are divided by a factor proportional to the edge sensing term. When $\kappa=0$, the rational filter acts as the following linear filter.

$$\hat{\Delta}_k = w(\Delta_{k-1} + \Delta_{k+1}) + (1 - 2w)\Delta_k \tag{5}$$

The sum of the coefficients or weights of the above filter is one. The filter shows low pass behavior for $0 < w < 1/3$. For w=1/3, the filter becomes a moving average filter. When $\kappa \rightarrow \infty$, the filter has no effect, and $\hat{\Delta}_k \cong \Delta_k$. For intermediate values of κ, the $(\Delta_{k-1} - \Delta_{k+1})^2$ term perceives the presence of a detail and accordingly reduces the smoothing effect of the operator. This filter has good edge preserving capability, which is required for health monitoring problems. It has a time delay of one point due to the forward predictor point Δ_{k+1}.

Median Filter: The median filter belongs to a group of nonlinear filters called order statistics filter which are based on sorting of the signal sample. The order statistics filters select one of the sorted neighborhood samples of the input signal vector in each sampling period. The three point median filter can be written as [4]

$$\hat{\Delta}_k = median(\Delta_{k-1}, \Delta_k, \Delta_{k+1}) \qquad (6)$$

The median filter shown above has a one point time delay and uses a forward and backward predictor. The median filter is widely used in signal and image processing for the capability of outlier removal while preserving edges. However, the median is a selection filter which means that its output is limited to one of the input samples. Therefore, the median is not very good at removing Gaussian or random noise since each element of the input sample contains random noise. However, the median filter is conceptually very simple though long length median filters involve sorting operations that can be computationally expensive. Therefore, in this paper, we use only three point median filter to avoid forward point requirements and keep the computational expenses down.

Median Plus Rational Filter: This filter preprocesses the signal with a median filter before using the rational filter and is shown in schematic form in Figure 2 inside the dotted lines. We propose and use this combination in the paper for denoising of gas path measurement deltas. First, the measurement delta is passed through the median filter.

$$\begin{aligned} y_{k-1} &= median(\Delta_{k-2}, \Delta_{k-1}, \Delta_k) \\ y_k &= median(\Delta_{k-1}, \Delta_k, \Delta_{k+1}) \\ y_{k+1} &= median(\Delta_k, \Delta_{k+1}, \Delta_{k+2}) \end{aligned} \qquad (7)$$

During this phase, the outliers in the data are removed. In the next phase, the median preprocessed data is sent through the rational filter. The rational filter can be defined using the outputs of the median filter from Eq. 7 as

$$\begin{aligned} d_k &= \kappa\,(y_{k-1} - y_{k+1})^2 + \frac{1}{w} \\ \hat{\Delta}_k &= \frac{y_{k-1} + y_{k+1} + y_k[d_k - 2]}{d_k} \end{aligned} \qquad (8)$$

The evaluation of the filtered value using the above formulas is very fast if one defines the denominator of the rational filter as a variable d_k and then uses it for the calculation of the "median plus rational" filter output as shown above. The three point median involves a simple sorting operation of three numbers and then taking the middle value. Therefore, the "median plus rational" approach is computationally efficient with a two point time delay requiring points within a five point window including the k-2, k-1, k, k+1 and k+2 discrete time points.

In this study, κ is been fixed at 0.01 and w at 0.16 as suggested by Ramponi who obtained these values as optimal for a signal contaminated with Gaussian noise [6]. This is a good assumption for the "median plus rational" approach as the data is first subjected to a median filter which removes outliers and the rational filter is then used on a signal with trend shift and Gaussian noise.

V. NUMERICAL RESULTS

Numerical results are obtained using the test signal shown in Figure 3 and 4 which contain the step signal and the ramp signal simulating abrupt fault and engine deterioration respectively. The noisy data shown in these figures uses α =0.2 and added outliers which were discussed earlier. Figure 3 and 4 also shows the results of processing the noisy signal using the rational and median plus rational filters, respectively.

From Figure 3, we see that the rational filter is able to preserve the trend shift while reducing Gaussian noise to some extent, but is unable to discard the outliers. The "median plus rational" approach results in the outliers being removed from the signal and Gaussian noise being reduced while preserving the trend shift. Figure 4 shows that for a linear signal, the rational filter is unable to remove outliers. However, the "median plus rational" approach results in outlier removal along with some removal of Gaussian noise. The visual quality of the signals is considerably improved after the application of the "median plus rational" filter. Since monitoring "trend plots" of gas path measurement deltas form an important diagnostic tool for airline powerplant engineers, the use of the nonlinear filters for smoothing the data can greatly increase their capability of finding faults by visual inspections of the gas path sensor data itself.

The above results are qualitative and provide visual information about the filters. However, they represent only one of many possible noisy data samples. To obtain quantitative results, 1000 samples of noisy data are created about the ideal step and ramp signals in Figures 3 and 4 and the noise reduction after filtering is calculated. Tables 3 and 4 show the noise reduction based on the mean square error (*MSE)* for the step signal and the ramp signal, respectively. The noise level added to the ideal signal varies from low (α =0.10) to high (α=0.40). The rational filter reduces noise by 47 percent for the step signal and by about 48 percent for the ramp signal. The noise reduction is almost constant across the noise levels. The median filter reduces noise level by 65-86 percent for the step signal and 70-96 percent for the ramp signal. For the median filter, the noise reduction decreases with increasing levels of Gaussian noise in the data. The median filter works better when the data has outliers and low levels of Gaussian noise. The “median plus rational” filter reduces noise by 73-88 percent for the step signal and 77-96 percent for the ramp signal. The “median plus rational” filter gives more noise reductions than the median filter at all noise levels. However, the advantage increases at higher levels of Gaussian noise where the random noise removing ability of the rational filter is useful.

The above results show that for gas path measurement data which often contain high levels of outliers and random noise, it is advantageous to use the “median plus rational” filter to preprocess the data before performing fault detection and isolation functions. Using these filters for real data is a subject of future work.

VI. Concluding Remarks

Simulated health monitoring test signals are used to evaluate the denoising capability of nonlinear filters for smoothing gas turbine health signals. Linear filters such as the moving average which are widely used in the gas turbine industry tend to smooth out the sharp edges in the signal which is often a precursor to an abrupt fault. Linear filters are also not good at removing outliers. The effect of both Gaussian noise and outliers of non-Gaussian origin are considered. The nonlinear filters used in this study are the rational filter and median filter.

The median and rational filters show good edge preservation capability. However, the rational filter is not good for outlier removal though it preserves the edges in the health signal. If the data is preprocessed by a median filter and then sent through a rational filter, both outliers and Gaussian noise is removed while preserving the edges in the signal which are often precursors to abrupt faults.

The “median plus rational” filter results in noise reduction of 73-96 percent for the noisy signals and is also conceptually simple and computationally efficient when implemented in a small window of three points as suggested in this paper. Furthermore, the filter has a two point time delay, making it suitable for jet engine diagnostics where few points are obtained for each flight and the cost of transmitting additional points is high. The “median plus rational” filter is therefore recommended for preprocessing gas turbine measurement deltas before performing fault detection and isolation functions.

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Table 1. Fingerprints for selected gas turbine faults η=-2%

Faults	ΔEGT (C)	ΔWF %	$\Delta N2$%	$\Delta N1$%
High Pressure Compressor	13.60	1.60	-0.11	0.10
High Pressure Turbine	21.77	2.58	-1.13	0.15
Low Pressure Compressor	9.09	1.32	0.57	0.28
Low Pressure Turbine	2.38	-1.92	1.27	-1.96
Fan	-7.72	-1.40	-0.59	1.35

Table 2. Signal to noise ratios for fingerprints of gas turbine faults in Table 1

Faults	ΔEGT	ΔWF	$\Delta N2$	$\Delta N1$
High Pressure Compressor	3.215	3.2	0.65	0.40
High Pressure Turbine	5.15	5.16	6.65	0.60
Low Pressure Compressor	2.14	2.64	3.35	1.12
Low Pressure Turbine	0.56	3.84	7.47	7.84
Fan	1.82	2.80	3.47	5.40

Table 3. Noise reduction with filters for engine abrupt fault signal based on MSE

α	0.10	0.15	0.20	0.25	0.30	0.35	0.40
Rational	46.93	46.95	46.99	47.05	47.13	47.21	47.29
Median	86.39	83.21	79.41	75.36	71.43	67.94	65.04
Median+Rational	88.37	85.96	83.11	80.11	77.23	74.68	72.58

Table 4. Noise reduction with filters for engine deterioration signal based on MSE

α	0.10	0.15	0.20	0.25	0.30	0.35	0.40
Rational	48.44	48.39	48.34	48.3	48.27	48.25	48.23
Median	95.38	91.56	86.91	82	77.31	73.13	69.60
Median+Rational	96.18	93.38	89.96	86.33	82.85	79.74	77.11

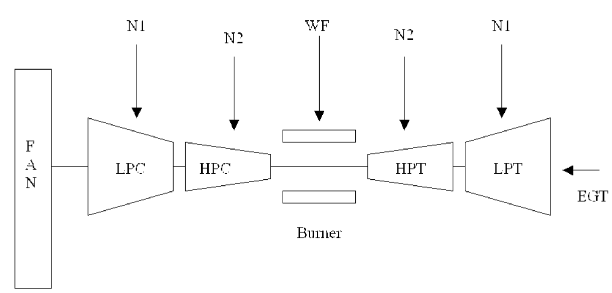

Figure 1. Schematic view of turbofan gas turbine engine modules and sensors

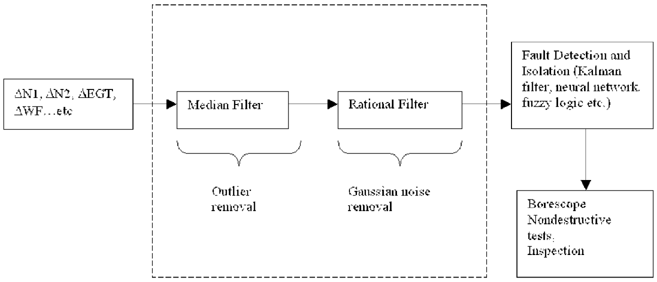

Figure 2. Schematics of noise and outlier removal in gas turbine diagnostics process

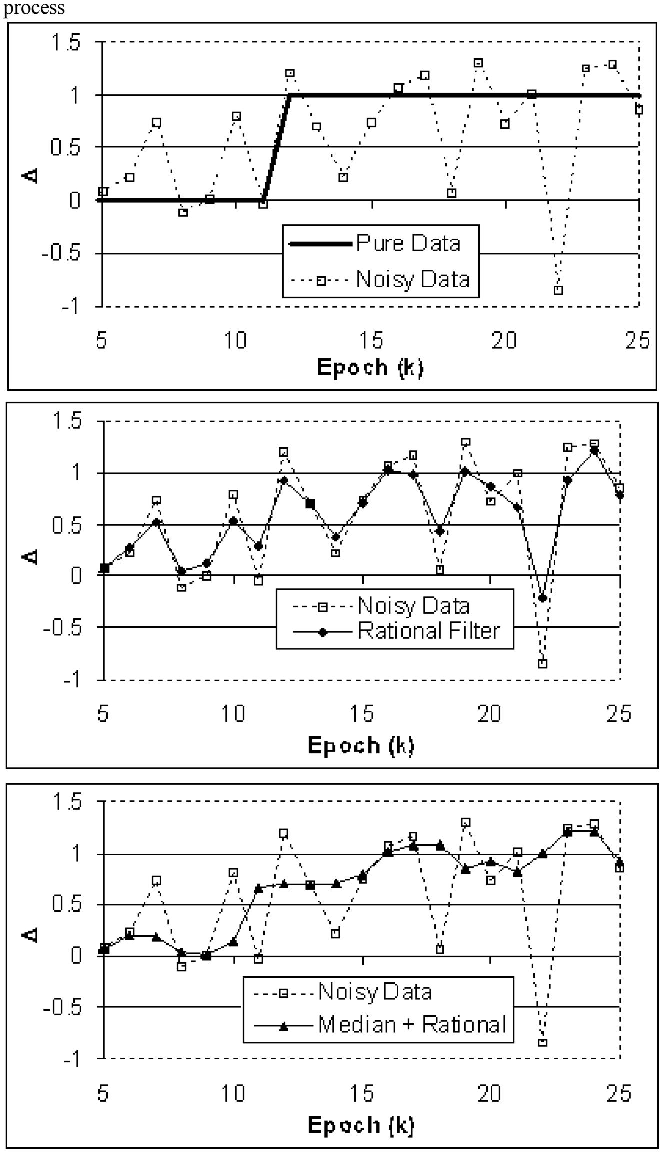

Figure 3. Ideal, noisy and filtered signal for engine “abrupt fault”

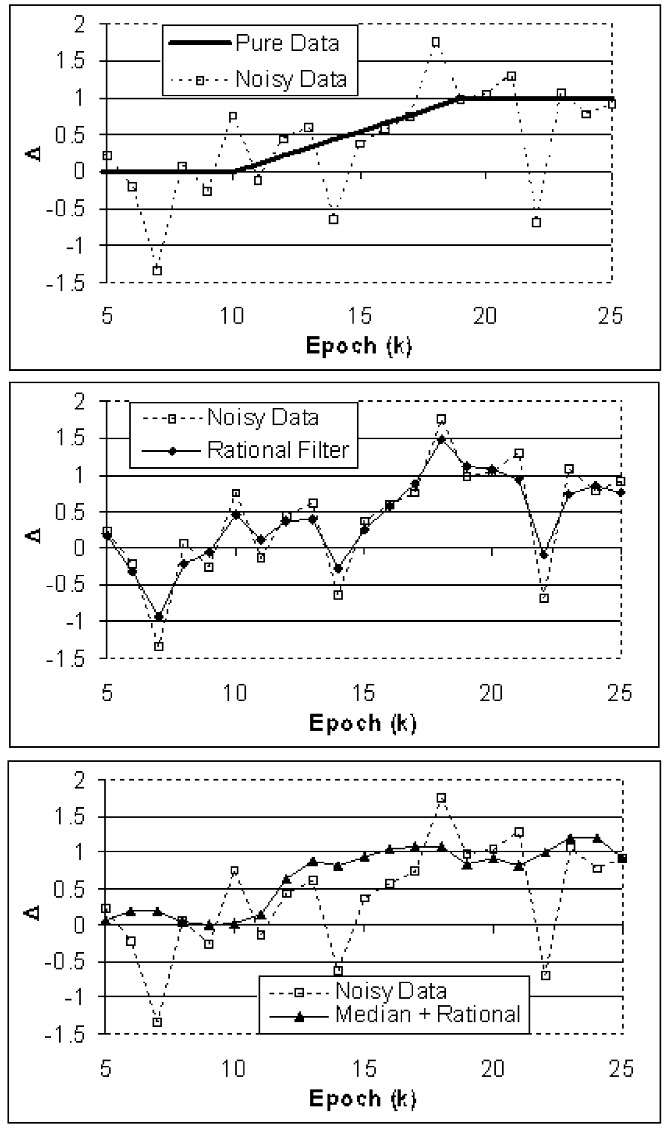

Figure 4. Ideal, noisy and filtered signal for engine “deterioration”