Matched Filtering-Based Sensor Fault Classification for Structural Health Monitoring Systems

JAN-HAUKE BARTELS, GUOFENG QIAN and MICHAEL D. TODD

ABSTRACT

Structural health monitoring (SHM) systems rely on sensor networks to assess the condition of engineering structures designed for long-term operation. Over time, structures such as wind turbine towers or bridges may experience degradation-related damage, while the monitoring systems themselves age and become less reliable. This aging can lead to sensor faults that generate plausible yet inaccurate data, potentially causing misinterpretations of structural integrity and even catastrophic failures. Therefore, distinguishing between sensor faults and actual structural damage is crucial for ensuring the long-term reliability of SHM systems.

A key challenge is the diversity of sensor fault types, which must first be classified to enable effective compensation. This study introduces a matched filtering approach to address this issue. Sensor fault types, such as bias and drift within a sensor network, are analyzed using matched filtering to classify them effectively.

The proposed classification method is validated on a real-world support structure with synthetic measurement data, a 9-meter-high lattice mast exposed to real environmental conditions. The results demonstrate that sensor faults can be accurately classified. A key advantage of this approach is that precise classification enables more accurate sensor fault compensation. Enhancing the robustness of SHM systems will significantly improve the reliability of data-driven structural assessments, a crucial aspect for ensuring the longevity of critical infrastructure.

Keywords: Acceleration measurements, matched filtering, sensor aging, sensor fault classification, sensor fault diagnosis, structural health monitoring

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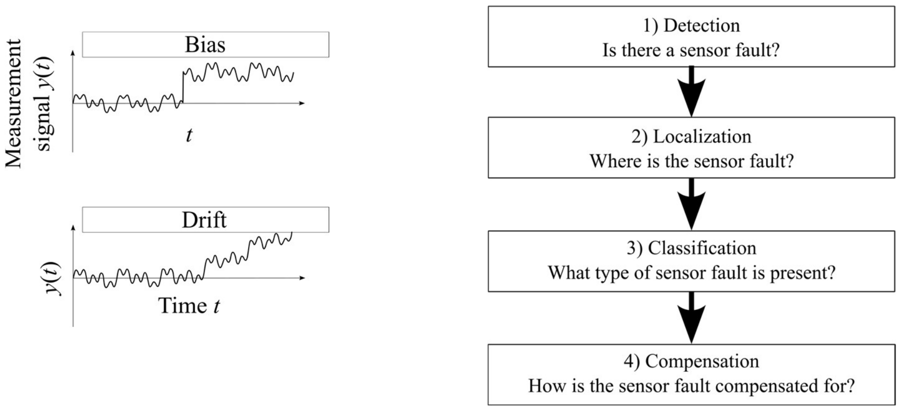
MOTIVATION

In recent years, the increasing accuracy of sensors has led to their widespread use in structural health monitoring (SHM) of complex systems like bridges and wind turbines [1,2]. These structures are designed for long service lives – 20 years for wind turbines and 100 years for bridges – during which deterioration-related damage and changing environmental conditions occur. However, the monitoring systems themselves also degrade over time, becoming less reliable [3]. Detecting sensor faults due to this aging process is particularly challenging because components degrade gradually, producing plausible but corrupted data. Using such corrupt data can lead to misinterpretation of structural performance and failure to detect structural damage. Therefore, methods are needed to identify aging phenomena in monitoring systems, ensuring robust performance throughout the structure's life cycle.



(**a**) (**b**)

Figure 1. Typical sensor fault types in structural health monitoring systems in (**a**), and the sensor fault diagnosis (SFD) process in (**b**).

To distinguish between sensor faults and structural damage, it is essential to define sensor faults as conditions where a loss of functionality occurs in the measurement system, leading to data that no longer accurately reflects the monitored phenomenon [4]. Therefore, a process has been developed to diagnose these sensor aging processes, see Figure 1 (**b**). This sensor fault diagnosis (SFD) involves four steps: (i) Detection, (ii) localization, (iii) classification, and (iv) compensation [5]. This paper focuses on sensor fault classification in sensor networks. While previous works, such as those by Kullaa [6], Bartels et al. [7], and Lydakis et al. [8], primarily address the step of sensor fault detection and localization, no specific work is known in the literature that deals exclusively with the classification of sensor faults. This step is essential to carry out meaningful compensation of ageing effects in the measurement system.

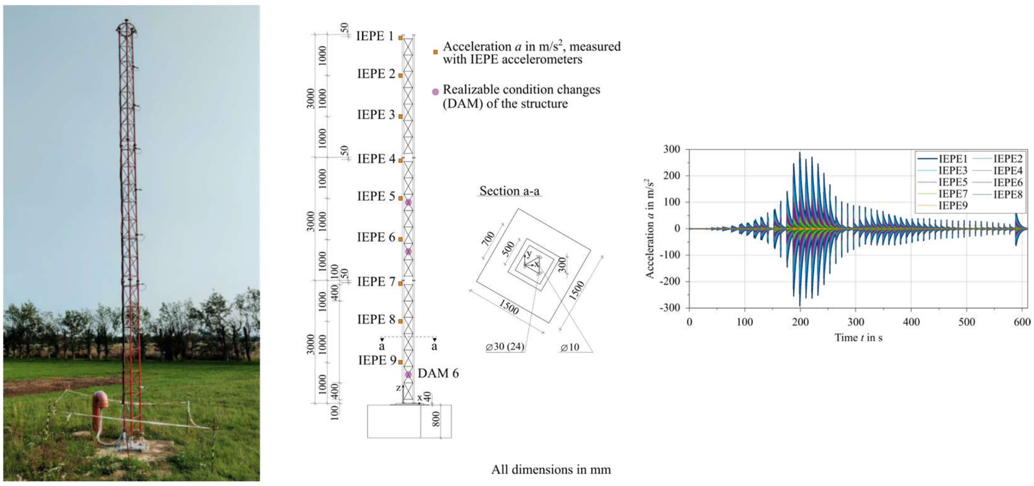
To overcome this issue, we propose a matched filtering approach for sensor fault classification. This allows more robust SHM systems to be used, ensuring their reliability over the life of the structure. For this purpose, a simple lattice mast structure with an accelerometer-based SHM system is used to conduct a parameter study with respect to the ability to classify sensor faults.

EXPERIMENTAL SETUP AND METHODOLOGY

Experimental Setup

The numerical model for the parameter study represents a real-world steel lattice mast, which is shown in Figure 2Figure 4 (**a**). The load-bearing structure and raw data acquisition were conducted by the Institute of Statics and Dynamics at Leibniz University Hanover, Germany. Detailed dataset documentation and structural damage analysis are available in [9] and [10]. These data form the basis for the finite element model and the sensor fault classification approach in this study. The test structure, located 20 km south of Hanover, consists of a 9-meter-high steel lattice mast on a reinforced concrete foundation. It comprises three identical 3 m segments, each with three tubular legs forming an isosceles triangular cross-section. The mast weighs approximately 90 kg without sensors and is equipped with an accelerometer-based SHM system. Each segment has seven bracing levels and short connecting sections, assembled with M10 bolts. The mast is anchored to a 1.50 × 1.50 × 0.80 m³ reinforced concrete foundation using an anchor plate with 12 M12 bolts, ensuring a rigid base.

To distinguish structural damage from sensor faults, two reversible damage scenarios (DAM) are implemented by removing diagonal bracings equipped with threaded rods. Nine acceleration sensors measure the structural response, with damage scenarios and sensor locations shown in the drawing of Figure 2 (**a**). A nearby weather station records environmental factors like temperature, humidity, and wind, which can influence structural response. Since data normalization is beyond this study's scope, normalized measurements are assumed. This assumption is ensured by using synthetic data that has been numerically generated independently of environmental influences. The finite element model, built using Dlubal RSTAB finite element software, is updated with real data and subjected to time-dependent excitation at the mast's free end.



(**a**) (**b**)

Figure 2. Validation structure based on Wernitz et al. [10]. (**a**) Photo and drawing of the lattice mast; (**b**) synthetic raw data from the healthy measurement system and healthy structural state.

The numerical model is used to generate synthetic data, which has the advantage of providing directly comparable, reproducible data. The excitation lasts 600 seconds with a frequency sweep from 0.1 Hz to 10 Hz in 0.2 Hz steps. The sampling rate is 40 Hz, and the raw data signal is overlaid with white noise $X \sim \mathcal{N}(\mu, \sigma^2) = \mathcal{N}(0, 2.56 \cdot 10^{-4}\ \mathrm{m/s^2})$, which was quantified with the aid of laboratory tests [11]. Figure 2 (**b**) shows the raw data for the reference state.

Sensor signals (IEPE1 to 9) exhibit similar acceleration trends over time, differing mainly in amplitude. For the parameter study of the sensor fault classification method using matched filters, sensor faults are integrated into the respective sensor measurement data. The different sensor faults are always integrated into the measurement signal of IEPE5. The magnitude of the sensor faults and their occurrence times are listed in Table I.

Table I. Description of realized sensor fault types within the analysis of this study.

Measurement system and structural condition	Amplitude	Period
Healthy	As shown in Figure 2	-
Bias $y_{\mathrm{SF}}(t) = y(t) + b + n(t)$	$b \in \{1\sigma; 2\sigma; 3\sigma\}$	$t \in \{305s; 610s\}$
Drift $y_{\mathrm{SF}}(t) = y(t) + b \cdot t + n(t)$	$b \in \{0; 1\sigma\}$	$t \in \{305s; 610s\}$
DAM6 Partial	One diagonal removed in level DAM 6	-
DAM6 Full	All diagonals in level DAM 6 removed	-

A parameter study is conducted, where five different parameters are varied. The healthy measurement system and structural condition of the lattice mast form the reference basis for the analysis. The sensor faults, bias and drift, as well as two damaged structural states, “DAM6 Partial” and “DAM6 Full”, are added.

Matched Filtering for Sensor Fault Classification

The classification of sensor faults is a crucial step in SFD, as it provides additional information about the nature and cause of the sensor fault. This information supports the interpretation of sensor readings and facilitates decision-making regarding appropriate compensation measures. For instance, temporary sensor faults such as an increase in noise caused by electromagnetic interference require different mitigation strategies than a bias, where correct classification enables compensation of the sensor behavior and thus improves data quality.

Due to the characteristic signal features associated with different types of sensor faults (see Figure 1 (**a**), the development of so-called matched filters appears to be a promising approach for sensor fault classification. Matched filters require specific knowledge about the signal whose occurrences are to be detected. This requirement can be utilized positively in SFD, as different types of sensor faults exhibit distinct signal characteristics that can be exploited for improved sensor fault classification.

A matched filter is a fundamental tool in electrical engineering used to extract known wavelets from a noisy signal. It maximizes the signal-to-noise ratio (SNR), i.e., the ratio between the signal energy and the noise energy, thereby enhancing the clarity and interpretability of the signal information. This is achieved by cross-correlating the signal with a wavelet. Wavelets are mathematical functions specifically suited for analyzing and processing signals, particularly when dealing with non-stationary or time-varying signals [12].

Considering the block diagram shown in Figure 3, where the input signal $x(t)$ is defined as the sum of a signal component $s(t)$ and a noise component $w(t)$, the objective is to design a filter $h(t)$ that maximizes the SNR of the output signal $y(t)$.

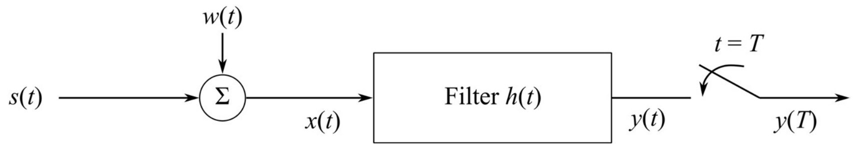


Figure 3. Block diagram for the principle of the optimum filter.

To maximize the SNR, it is necessary to determine the energy of a signal over time. This is achieved by applying a filter $h(t)$. The central question that arises is how the impulse response of the filter should be defined, i.e., how the filter itself should be designed.

The input signal $x(t)$ is processed through the predefined filter $h(t)$, resulting in the output signal $y(t)$. When analyzing the output of the filter at a specific time $t = T$, the output signal $y(T)$ is obtained.

This process is based on the mathematical operation of convolution between the input signal $x(t)$ and the filter $h(t)$. Convolution combines two functions by multiplying one function pointwise with a mirrored and shifted version of the other and integrating over all time points, thereby capturing the interaction between the two functions [13]. Formally, the convolution of two functions $x(t)$ and $h(t)$ is expressed as:

$$(x * h)(t) = \int_{-\infty}^{\infty} x(\tau) \cdot h(t - \tau)\, d\tau. \tag{1}$$

Convolution is a fundamental operation in signal processing used to analyze a signal for characteristic patterns or structures, such as in the application of a matched filter.

In this process, the function $h(t)$ is first mirrored along the time axis (transforming $h(t)$ into $h(-\tau)$ and then shifted by a certain amount (yielding $h(t - \tau)$. It is then multiplied pointwise with another function $x(t)$. The integral sums these products over all time points τ, resulting in the convolution output at time t.

This procedure helps to determine how well $x(t)$ and $h(t)$ match at a specific time point. Mathematically, this operation is described by the equation:

$$y(T) = \big(s(t) * h(t)\big)\,|_{t=T} + w(t) * h(t)\,|_{t=T}, \tag{2}$$

where the signal $s(t)$ and the additive white noise $w(t)$ are convolved with the filter $h(t)$ and analyzed at time $t = T$. This equation can be simplified to:

$$y(T) = Y_s(T) + Y_n(T). \tag{3}$$

Accordingly, the SNR can be calculated as:

$$\mathrm{SNR} = \frac{y_s^2(T)}{\mathrm{E}[y_n^2(T)]}. \tag{4}$$

It is important to note that the expected value of the squared noise signal is not zero but represents the energy content of the noise. The SNR is maximized when the filter $h(t)$ takes the form of the signal $s(t)$, that is, when:

$$h(t) = s(T - t), \tag{5}$$

as shown in [14]. This principle is illustrated using a basic example. A rectangular pulse, as shown in Figure 4, is used for this purpose. The signal $s(t)$ is convolved with the filter $h(t)$, where both signals have identical shapes. The result of convolving two rectangular pulses is a triangular waveform with its maximum at the sampling time T. This can be explained by the integration of the signal's energy: at time T, the convolution result from $s(t)$ and the matched filter $h(t)$ fully overlaps, thus maximizing the SNR.

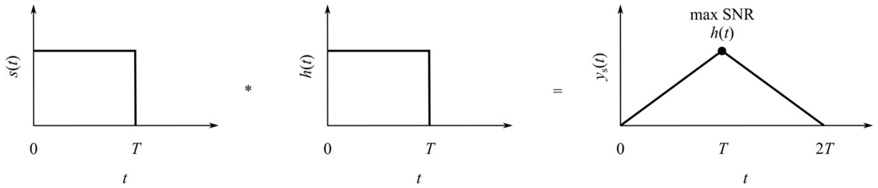


Figure 4. Example for the application of a matched filter.

The mathematical derivation of this result is extensively discussed in several signal processing references, such as Ziemer and Tranter (2009) and Kay (1988). A detailed derivation of the generalized optimum filter is omitted here, and the reader is referred to the relevant literature [14,15]. In the field of SHM, the use of matched filtering methods has been successfully addressed in a few studies. Sharma et al. (2018) [16] used a matched filter combined with wavelet transformation to enhance the detection of cracks in structural components by improving the SNR of Lamb wave signals. Lange et al. (2024) [17] demonstrated the effectiveness of matched filtering for identifying wire breaks in prestressed tendons of wind turbines under high-noise conditions, where conventional detection methods often fail. Similarly, Shearer (1994) [18] applied matched filters to long-term seismogram data, using stacked earthquake recordings to detect previously unknown seismic events with improved SNR.

A commonality across these research areas is that matched filters have been applied in SHM for condition assessment of structures. The matched filters have not yet been systematically employed for the diagnosis of sensor faults. This paper addresses this research gap by investigating the applicability of matched filters for the reliable classification of sensor faults.

PARAMETER STUDY AND DISCUSSION

In this parameter study, the matched filter technique is applied to different building and measurement system conditions to see whether qualitative shape criteria and quantitative, shape-based features enable a classification of sensor faults. For this purpose, the two sensor faults, bias and drift, a healthy measurement system and structural condition, and three structural damage conditions are analyzed concerning the matched filter output. In real-world measurements, biases and drifts exhibit highly similar characteristics. Both sensor faults manifest primarily in the low-frequency domain and can produce comparable responses. Consequently, classifying bias and drift sensor faults purely based on signal form becomes challenging, as both may generate slowly varying or quasi-constant correlation outputs. Advanced feature extraction methods, such as signal energy or skewness analysis, could therefore be essential to enable reliable sensor fault classification.

In this study, a bias signal was selected as the wavelet for matched filtering. The rationale lies in the objective to emphasize differences in the form of the matched filter output rather than reproducing the exact fault profile. The bias wavelet is shown in Figure 5; it starts at 20 seconds, spans 80 seconds, and has an amplitude of 0.5.

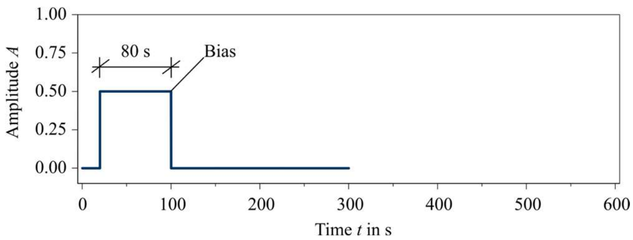
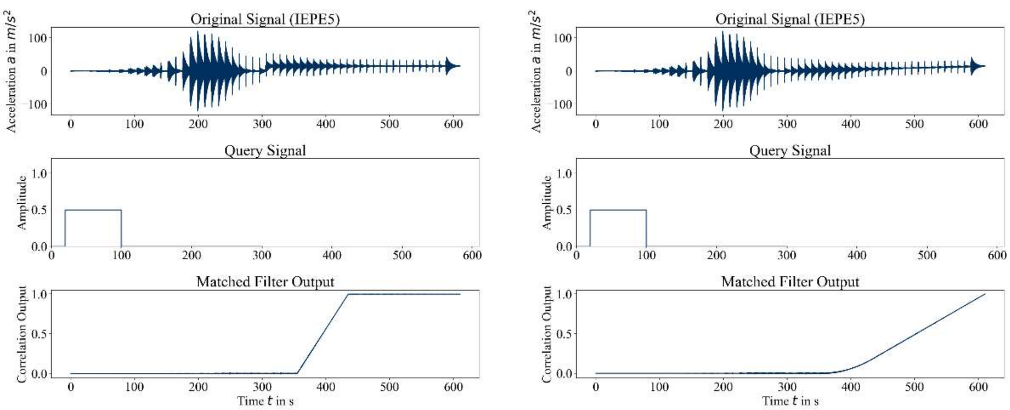


Figure 5. Bias as the wavelet for sensor fault classification.

Using a simple bias wavelet enhances the robustness of the analysis, stabilizes the extracted features (signal energy, Pearson correlation between matched filter output and wavelet, and skewness), and avoids overfitting specific fault shapes. The differing dynamic behaviors of bias and drift faults are effectively captured in the matched filter output form. Instead of applying a fixed threshold to identify the mere presence of a fault, the shape and characteristics of the matched filter output are evaluated to classify these specific sensor faults.

For the states described in Table I, which include synthetic healthy, bias, and drift sensor conditions as well as structural damage scenarios (DAM6 Partial and DAM6 Full) generated via finite element modeling, the raw data time signals are convolved with the wavelet shown in Figure 5 to generate matched filter outputs. Figure 6 illustrates the resulting matched filter outputs for bias and drift conditions.



(**a**) (**b**)

Figure 6. Raw data signal, wavelet as query signal, and normalized matched filter output for (**a**) bias and (**b**) drift.

The matched filter outputs were analyzed regarding their qualitative form and based on three shape-based features: signal energy (calculated according to Parseval's theorem), the Pearson correlation coefficient between the wavelet and the matched filter output, and the skewness of the matched filter output. The results for all six examined conditions are summarized in Table II.

Table II. Examined states in the parameter study for sensor fault classification.

	Qualitative form of output	Signal energy	Pearson correlation	Skewness
Healthy	Like sensor input	658.5	0.344	−0.820
Bias 1 Sigma	See Fig.6	8045.5	0.004	0.415
Drift 1 sigma	See fig. 6	2871.6	0.247	−0.776
DAM 6 Partial	Like sensor input	668.6	−0.308	0.928
DAM 6 Full	Like sensor input	555.1	−0.351	0.6814

As shown in Figure 6, the qualitative form of the matched filter output for a bias sensor fault differs markedly from that of a drift sensor fault. In the bias case, the output can be segmented into three regions (constant near zero, linearly increasing, and constant near one), whereas the drift fault exhibits a smooth, continuous transition from zero to one.

The shape-based metrics quantitatively confirm this observation. Signal energy is significantly higher for the bias fault in comparison to all other stated, since both the wavelet and the actual fault correspond to a bias. The signal energy for the drift fault is lower but still considerably higher than for healthy and damaged structure conditions (DAM6 Partial and DAM6 Full).

Interestingly, the Pearson correlation coefficient is particularly low in the bias case. This is a natural consequence of the quasi-constant nature of both the wavelet and the matched filter output: since Pearson correlation primarily measures linear co-variation, nearly flat signals yield low correlation values despite high structural similarity.

Although skewness was initially considered a promising shape-based feature for distinguishing bias and drift, practical analyses revealed its limited discriminative power. Noise and signal fluctuations obscure the theoretically expected asymmetry, resulting in similar skewness values across all examined conditions. Therefore, skewness alone is not sufficient for reliable fault classification.

Overall, the results demonstrate that, particularly the signal energy and the qualitative form of the matched filter output, are suitable for the classification of sensor faults. However, it is important to note that further sensitivity analyses, including variations of wavelet parameters (e.g., amplitude, duration) and fault characteristics (e.g., severity, onset), should be conducted to further substantiate these findings.

CONCLUSION AND OUTLOOK

Sensor faults in structural health monitoring (SHM) systems pose a significant challenge by compromising monitoring quality and potentially leading to substantial economic losses due to inaccurate measurement data. Despite the critical importance of SFD, it has received limited attention in SHM research to date. This paper addresses this gap by introducing the matched filter approach for sensor fault classification. The main findings of the study are as follows:

- The qualitative form of the matched filter output enables the classification of bias and drift sensor faults based on structural signal characteristics.
- Signal energy provides a robust quantitative shape-based feature to distinguish between sensor faults and both healthy and unhealthy structural conditions.
- Pearson correlation and skewness, although initially considered promising features, show limited discriminative power and should be used cautiously in sensor fault classification.

The results demonstrate that matched filtering is a viable method for the classification of sensor faults. Future work will extend the current analysis by systematically varying additional parameters, such as the shape and amplitude of the wavelet, as well as the severity of the sensor faults. Nevertheless, the findings already highlight that the matched filter technique can significantly enhance the robustness of SHM systems by enabling sensor fault classification. Combined with the other steps in SFD, the method provides more accurate structural condition assessments, contributing to better decision-making and the long-term sustainability of critical infrastructure.

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