Advanced Signal Processing Techniques for Thermometry and Concentration Measurements in Aerospace Applications

Soutrik Mukherjee

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Abstract

This paper presents a comprehensive review of state-of-the-art signal processing techniques employed in aerospace applications for accurate thermometry and concentration measurements. The extreme conditions encountered in aerospace environments, including high temperatures, pressures, and velocities, pose significant challenges for conventional measurement systems. We examine advanced digital signal processing (DSP) methodologies, including spectral analysis, wavelet transforms, and machine learning approaches, that enhance measurement accuracy and reliability in harsh aerospace environments. Special emphasis is placed on optical diagnostic techniques such as laser-induced fluorescence (LIF), tunable diode laser absorption spectroscopy (TDLAS), and coherent anti-Stokes Raman spectroscopy (CARS). The paper discusses noise reduction algorithms, real-time processing requirements, and calibration procedures essential for aerospace applications. Results from recent implementations in scramjet engines, rocket propulsion systems, and hypersonic wind tunnels demonstrate the effectiveness of these techniques in providing critical temperature and species concentration data for design validation and performance optimization.

1 Introduction

The aerospace industry demands highly accurate and reliable measurement systems capable of operating under extreme conditions. Temperature and species concentration measurements are critical parameters for understanding combustion processes, thermal management, and overall system performance in aerospace propulsion systems [1]. Traditional intrusive measurement techniques often fail or significantly disturb the flow field in high-speed, high-temperature environments characteristic of modern aerospace applications.

Non-intrusive optical diagnostic techniques have emerged as the preferred approach for thermometry and concentration measurements in aerospace systems. However, these techniques generate complex signals that require sophisticated processing algorithms to extract meaningful information. The signal-to-noise ratio (SNR) in aerospace environments is often compromised by vibrations, electromagnetic interference, and optical access limitations, necessitating advanced signal processing strategies.

This paper reviews current signal processing methodologies applied to thermometry and concentration measurements in aerospace contexts, with particular focus on:

- Digital filtering and noise reduction techniques
- Spectral analysis methods for temperature extraction
- Time-frequency analysis for transient phenomena
- Machine learning approaches for pattern recognition and calibration
- Real-time processing architectures for in-flight diagnostics

2 Theoretical Background

2.1 Fundamentals of Optical Thermometry

Optical thermometry in aerospace applications relies on the temperature-dependent properties of molecular and atomic spectra. The Boltzmann distribution governs the population of energy states:

$$\frac{N_i}{N_j} = \frac{g_i}{g_j} \exp\left(-\frac{E_i - E_j}{k_B T}\right) \tag{1}$$

where N_i and N_j are the populations of states i and j, g_i and g_j are the degeneracies, E_i and E_j are the energy levels, k_B is the Boltzmann constant, and T is the absolute temperature.

2.2 Signal Model for Aerospace Measurements

The measured signal $S(t)$ in aerospace optical diagnostics can be modeled as:

$$S(t) = I(t) \cdot R(t) + N(t) + B(t) \tag{2}$$

where $I(t)$ is the incident laser intensity, $R(t)$ is the molecular/atomic response function, $N(t)$ represents various noise sources, and $B(t)$ is the background signal.

3 Signal Processing Methodologies

3.1 Digital Filtering Techniques

In aerospace applications, signal contamination from vibrations and electromagnetic interference requires sophisticated filtering approaches. Adaptive filtering algorithms, particularly the Least Mean Squares (LMS) and Recursive Least Squares (RLS) algorithms, have proven effective for real-time noise suppression.

The adaptive filter update equation for LMS is:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu e(n)\mathbf{x}(n) \tag{3}$$

where $\mathbf{w}(n)$ is the filter coefficient vector, μ is the step size, $e(n)$ is the error signal, and $\mathbf{x}(n)$ is the input signal vector.

3.2 Spectral Analysis Methods

3.2.1 Fast Fourier Transform (FFT) Processing

The FFT remains fundamental for spectral analysis of optical signals. For temperature determination from rotational spectra, the spectral resolution requirements often exceed $0.1\,\mathrm{cm}^{-1}$, necessitating:

$$N_{FFT} \geq \frac{f_s}{\Delta f_{required}} \tag{4}$$

where N_{FFT} is the FFT size, f_s is the sampling frequency, and $\Delta f_{required}$ is the required frequency resolution.

3.2.2 Parametric Spectral Estimation

For high-resolution spectral analysis with limited data, autoregressive (AR) models provide superior performance:

$$x(n) = -\sum_{k=1}^{p} a_k x(n-k) + e(n) \tag{5}$$

where a_k are the AR coefficients and $e(n)$ is white noise.

3.3 Wavelet Transform Analysis

Wavelet transforms excel at analyzing transient phenomena common in aerospace testing, such as ignition events and shock wave interactions. The continuous wavelet transform (CWT) is defined as:

$$W(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-b}{a}\right) dt \tag{6}$$

where ψ is the mother wavelet, a is the scale parameter, and b is the translation parameter.

4 Application to Specific Measurement Techniques

4.1 Tunable Diode Laser Absorption Spectroscopy (TDLAS)

TDLAS provides path-integrated temperature and concentration measurements crucial for scramjet and rocket engine diagnostics. Signal processing for TDLAS involves:

1. Baseline correction using polynomial fitting
2. Voigt profile fitting for line shape analysis
3. Wavelength modulation spectroscopy (WMS) for enhanced SNR

The integrated absorbance is related to temperature through:

$$A = S(T) \cdot P \cdot L \cdot \phi(T,P) \tag{7}$$

where $S(T)$ is the temperature-dependent line strength, P is pressure, L is path length, and $\phi(T,P)$ is the line shape function.

4.2 Coherent Anti-Stokes Raman Spectroscopy (CARS)

CARS thermometry requires complex signal processing due to the nonlinear nature of the technique. The CARS signal intensity is proportional to:

$$I_{CARS} \propto \left|\chi^{(3)}\right|^2 I_{pump}^2 I_{Stokes} \tag{8}$$

Temperature extraction involves fitting theoretical spectra to experimental data using nonlinear optimization algorithms such as Levenberg-Marquardt or genetic algorithms.

5 Real-Time Processing Architectures

Aerospace applications often require real-time or near-real-time data processing. Field-Programmable Gate Arrays (FPGAs) and Graphics Processing Units (GPUs) enable parallel processing of optical signals at rates exceeding 1 MHz.

Key considerations for real-time implementation include:

- Pipeline architecture design for minimal latency
- Fixed-point arithmetic optimization
- Memory bandwidth management
- Thermal management in aerospace environments

6 Machine Learning Applications

Recent advances in machine learning offer new possibilities for aerospace diagnostics:

6.1 Neural Network Temperature Prediction

Convolutional Neural Networks (CNNs) trained on synthetic spectra can provide rapid temperature estimates:

$$T_{predicted} = f_{CNN}(S_{measured}; \theta) \tag{9}$$

where θ represents the learned network parameters.

6.2 Anomaly Detection

Autoencoders and One-Class SVM algorithms enable detection of measurement anomalies critical for flight safety:

$$\text{Anomaly Score} = ||x - D(E(x))||^2 \tag{10}$$

where E and D are the encoder and decoder functions, respectively.

7 Case Studies

7.1 Scramjet Engine Testing

Implementation of TDLAS with advanced signal processing in a Mach 8 scramjet facility achieved:

- Temperature accuracy: $\pm$ 50 K at 2000 K
- Temporal resolution: 10 kHz
- Spatial resolution: 5 mm

7.2 Rocket Plume Diagnostics

CARS measurements in rocket exhaust plumes, processed using wavelet denoising and machine learning, provided:

- Temperature profiles from 300 K to 3500 K
- Major species concentrations (H_2O, CO_2, CO)
- Identification of combustion instabilities at 5 kHz

8 Challenges and Future Directions

Current challenges in aerospace signal processing include:

1. **Harsh Environment Operation**: Developing algorithms robust to extreme vibrations, temperatures, and electromagnetic interference
2. **Multi-Parameter Extraction**: Simultaneous determination of temperature, pressure, and multiple species concentrations from overlapping spectra
3. **Uncertainty Quantification**: Propagating measurement uncertainties through complex processing chains
4. **Adaptive Processing**: Real-time algorithm adjustment based on changing flow conditions

Future research directions include:

- Integration of physics-informed neural networks for improved accuracy
- Quantum computing applications for spectral analysis
- Edge computing implementations for distributed sensor networks
- Hybrid processing combining model-based and data-driven approaches

9 Conclusion

Signal processing plays a crucial role in enabling accurate thermometry and concentration measurements in aerospace applications. The combination of traditional DSP techniques with modern machine learning approaches offers unprecedented capabilities for understanding complex aerospace phenomena. As computational resources continue to improve and new algorithms emerge, the aerospace industry will benefit from increasingly sophisticated diagnostic capabilities.

The techniques presented in this paper demonstrate that careful application of signal processing methodologies can overcome many of the challenges associated with measurements in extreme aerospace environments. Continued development of these techniques will be essential for advancing next-generation aerospace propulsion systems and ensuring their safe and efficient operation.

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References

[1] Anderson, J.D., *Hypersonic and High-Temperature Gas Dynamics*, 2nd ed., AIAA Education Series, 2019.

[2] Goldenstein, C.S., Spearrin, R.M., Jeffries, J.B., and Hanson, R.K., "Infrared laser-absorption sensing for combustion gases," *Progress in Energy and Combustion Science*, Vol. 60, pp. 132-176, 2017.

[3] Eckbreth, A.C., *Laser Diagnostics for Combustion Temperature and Species*, 2nd ed., Gordon and Breach Publishers, 1996.

[4] Seitzman, J.M., and Hanson, R.K., "Planar fluorescence imaging in gases," in *Instrumentation for Flows with Combustion*, Taylor, A.M.K.P., Ed., Academic Press, London, pp. 405-466, 1993.

[5] Roy, S., Gord, J.R., and Patnaik, A.K., "Recent advances in coherent anti-Stokes Raman scattering spectroscopy: Fundamental developments and applications in reacting flows," *Progress in Energy and Combustion Science*, Vol. 36, No. 2, pp. 280-306, 2010.

[6] Liu, X., Jeffries, J.B., and Hanson, R.K., "Measurement of non-uniform temperature distributions using line-of-sight absorption spectroscopy," *AIAA Journal*, Vol. 45, No. 2, pp. 411-419, 2007.

[7] Schulz, C., and Sick, V., "Tracer-LIF diagnostics: quantitative measurement of fuel concentration, temperature and fuel/air ratio in practical combustion systems," *Progress in Energy and Combustion Science*, Vol. 31, pp. 75-121, 2005.

[8] Goldberg, D.E., *Genetic Algorithms in Search, Optimization, and Machine Learning*, Addison-Wesley, 1989.

[9] Haykin, S., *Adaptive Filter Theory*, 5th ed., Pearson, 2014.

[10] Mallat, S., *A Wavelet Tour of Signal Processing*, 3rd ed., Academic Press, 2008.