Journal of Progress in Engineering
and Physical Science
ISSN 2709-4006
www.paradigmpress.org/jpeps
Volume 5 Number 1 March 2026

Deep Integration of Sensing Technology and Smart Manufacturing: Leading the Technological Upgrade of the Precision Manufacturing Industry

Huajun Liu[1]

[1] Shenzhen Fanhua Wuchuang Technology Co., Ltd., Shenzhen 518000, China
Correspondence: Huajun Liu, Shenzhen Fanhua Wuchuang Technology Co., Ltd., Shenzhen 518000, China.

doi:10.63593/JPEPS.2026.03.03

Abstract

Aiming at the technical bottlenecks in core links of the precision manufacturing industry, such as ultra-precision measurement and flexible production—including insufficient machining accuracy (traditional machining error ≥±0.025 μm), response lag (process adjustment delay >100 ms), and data silos—this paper proposes a full-chain integrated architecture of "perception-modeling-decision-execution". It reveals the signal crosstalk mechanism of multi-physics field coupled sensing units and systematically elaborates the deep collaboration mechanism between multi-parameter collaborative perception and digital twin, AI adaptive control, and industrial interconnection. By developing a four-parameter integrated MEMS sensing module based on frequency domain isolation, an attention mechanism-improved LSTM algorithm, and a cross-protocol adaptive conversion middleware, three core technological breakthroughs are achieved: (1) The measurement accuracy is improved from ±0.025 μm to ±0.006 μm (a relative increase of 76%), with a complex surface detection error ≤4.2 μm; (2) The response delay is reduced from >100 ms to 0.8 ms (a reduction of 99.2%), and the equipment fault early warning accuracy reaches 94.7%; (3) The changeover efficiency of flexible production lines is increased by 45%, and the product defect rate is reduced from 3.2% to 0.5% (a reduction of 84.4%). Empirical verification in three typical industrial scenarios shows that the integrated system increases production efficiency by 32%-48% and reduces comprehensive manufacturing costs by 18%-26%. The research results provide a systematic solution for the transformation of the precision manufacturing industry. Relevant technologies have formed 15 authorized patents and 11 software copyrights, possessing significant academic value and industrial application prospects.

Keywords: multi-parameter MEMS composite sensing, attention LSTM, weighted ICP, cross-protocol conversion, precision manufacturing, digital twin

1. Introduction

1.1 Research Background and Industrial Demand

The global precision manufacturing market size reached 782 billion US dollars in 2024, with a compound annual growth rate of 12.8% (Grand View Research, 2024). High-end industries such as aerospace and semiconductors have demanded nanoscale machining accuracy (≤±0.01 μm) (Pomeas, 2024; Liu C, et al., 2024). As the core perception component of smart manufacturing, current sensor applications face four major pain points: (1) Single-parameter detection cannot cover multi-physical quantity collaborative monitoring, with a synchronization error of >50 μs in discrete solutions; (2) Precision attenuation ≥10% under extreme working conditions, failing to adapt to the processing of aerospace components; (3) Data transmission and processing delay exceeding 100 ms, leading to lagging process adjustments; (4) Protocol incompatibility resulting in a data interaction rate of less than 60% (Chen W. & Liu J., 2023; Schmidt M, et al., 2019). According to a Deloitte report, related issues cause annual economic losses exceeding 50 billion US dollars (Deloitte, 2024). Constructing a deeply integrated system of sensing and smart manufacturing has become the key to technological upgrading.

1.2 Research Status at Home and Abroad and Research Gap

In the field of ultra-precision measurement, the axial resolution of spectral confocal sensors reaches 0.006 μm (Pomeas, 2024), and the fusion scheme of lidar and vision achieves a detection rate of >99% (Chen W. & Liu J., 2023); in process monitoring, the linearity error of force-sensitive array sensors is <3% (Chen W. & Liu J., 2023). In terms of integration technology, the combination of digital twin and sensing data increases turbine disk processing efficiency by 20% (Liu C, et al., 2024; Schmidt M, et al., 2019), and AI-driven predictive maintenance achieves an early warning accuracy of over 85% (Chen W. & Liu J., 2023). However, existing research has limitations: MIT's multi-parameter sensing module only supports 2 types of parameters with a volume >5 cm^3 (Rus D, et al., 2023); Stanford's AI algorithm has an inference time ≥50 ms (Zhang Y, et al., 2024); domestic research lacks full-chain architecture design and fails to solve the problem of precision stability under extreme working conditions (Liu J, et al., 2024).

Core Research Gaps: (1) Insufficient miniaturization and synchronization of multi-parameter integration, with a synchronization error >20 μs; (2) Unclear precision attenuation mechanism under extreme working conditions, with attenuation ≥10%; (3) End-to-end response delay exceeding 100 ms; (4) Digital twin mapping error >8% (Chen W. & Liu J., 2023; Schmidt M, et al., 2019).

1.3 Research Objectives and Innovations

This paper constructs an integrated system of "multi-sensor fusion-edge intelligence-industrial interconnection-digital twin", with the following core innovations:

(1) Four-parameter collaborative perception technology: Reveal the multi-physics field coupled crosstalk mechanism, propose frequency domain isolation and spatial layout optimization methods. To the best of our knowledge, temperature/pressure/vibration/morphology four parameters are integrated on a single MEMS chip for the first time, with a volume of 1.5 cm^3, synchronization error ≤5 μs, and precision attenuation ≤3% under extreme working conditions.

(2) Attention LSTM algorithm: Aiming at the non-stationary characteristics of industrial time series, propose an adaptive feature extraction mechanism to solve the gradient attenuation problem of standard LSTM. The computational complexity is $O(T \cdot d^2)$ (T is the sequence length, d is the feature dimension), with an early warning accuracy of 94.7% and an inference time of 187 μs.

(3) Cross-protocol conversion middleware: Realize seamless conversion of three major protocols based on a state machine, with a data interaction rate of 98% and a transmission delay ≤12 μs. Reliability is guaranteed through formal verification.

(4) Weighted ICP mapping algorithm: Derive the optimal weight function and convergence conditions, reduce the number of registration iterations by 39.9%, achieve a mapping error ≤3%, and an update frequency ≥100 Hz.

1.4 Paper Structure

Chapter 2 elaborates the integrated system architecture and core technical principles; Chapter 3 introduces the implementation of key technologies; Chapter 4 verifies performance through experiments; Chapter 5 compares with existing technologies; Chapter 6 summarizes and prospects future directions.

2. Overall Architecture and Core Technical Principles of the Integrated System

2.1 Overall Integrated Architecture Design

A four-layer integrated architecture of "perception layer-edge layer-interconnection layer-application layer" is constructed. Through functional collaboration and data closed-loop at all levels, full-chain optimization of "data collection-preprocessing-transmission-decision-execution" is realized. The core functions, key technical schemes, and performance indicators of each layer are shown in the following table:

Table 1. Detailed Description of the Four-Layer Integrated System Architecture

Architecture Layer	Core Functions	Key Technical Schemes	Core Performance Indicators	Hardware Support
Perception Layer	Four-parameter synchronous collection, anti-interference data acquisition, multi-physics field signal isolation	1. MEMS integration technology with frequency domain isolation and spatial layout optimization; 2. FPGA 100 MHz global clock synchronization; 3. Ceramic packaging + shielded wiring + differential transmission; 4. PTFE waterproof and breathable membrane for humidity protection	1. Multi-parameter collection synchronization error ≤5 μs; 2. Precision attenuation ≤3% in wide temperature range (-40℃~150℃); 3. Signal signal-to-noise ratio ≥45 dB; 4. Module volume ≤1.5 cm^3	Multi-parameter composite sensing module, FPGA synchronous control unit, AlN ceramic packaging components
Edge Layer	Data preprocessing (denoising/feature extraction), local intelligent decision-making, real-time control command generation	1. Improved wavelet threshold denoising algorithm; 2. Attention mechanism-improved LSTM model; 3. Fuzzy PID adaptive control algorithm; 4. Distributed deployment of edge computing	1. Data preprocessing time ≤200 μs; 2. Equipment fault early warning accuracy ≥94.7%; 3. Control response delay <1 ms; 4. Data compression ratio 9:1	STM32H743IGT6 MCU, edge computing gateway, local SD card storage module
Interconnection Layer	Cross-protocol data conversion, distributed clock synchronization, secure data transmission	1. Protocol adaptive conversion middleware (state machine model); 2. IEEE 1588 PTP clock synchronization	1. Support for PROFINET/EtherCAT/Modbus TCP protocols; 2. Clock synchronization accuracy ≤100 ns; 3. Data interaction rate ≥98%;	Xilinx Artix-7 FPGA, Gigabit Ethernet PHY chip (DP83848), LoRa module (SX1278)

		protocol; 3. AES-256 data encryption algorithm; 4. Wired (Ethernet) + wireless (LoRa) dual-mode transmission	4. Wired transmission delay ≤12 μs	
Application Layer	Digital twin process simulation, AI quality control, equipment predictive maintenance, global optimization decision-making	1. Weighted ICP digital twin mapping algorithm; 2. CNN defect detection model; 3. Equipment health index evaluation system; 4. Cloud-edge collaborative optimization platform	1. Digital twin mapping error ≤3%; 2. Product defect detection accuracy ≥99.2%; 3. Fault early warning lead time ≥32 h; 4. Global process optimization efficiency increased by 40%	Cloud server cluster, digital twin visualization platform, AI decision engine

Core Design Concept: The perception layer solves the problem of "multi-parameter high-precision synchronous collection", the edge layer solves the problem of "real-time intelligent decision-making and control", the interconnection layer solves the problem of "cross-protocol collaboration and secure transmission", and the application layer solves the problem of "global optimization and industrial landing". All layers form a collaborative optimization system through data closed-loop.

2.2 Core Technical Principles

2.2.1 Multi-Parameter Collaborative Perception Principle

A multi-physics field coupling model is established to reveal the signal crosstalk mechanism of temperature-pressure-vibration-morphology sensing units:

- Electromagnetic Equation (Morphological Sensing): $\nabla^2 u + \omega^2 \mu \varepsilon u = 0$, where u is the electric field intensity, ω is the angular frequency, μ is the permeability, and ε is the permittivity;
- Mechanical equation (pressure/vibration sensing): $\sigma = E\varepsilon$, where σ is stress, E is the elastic modulus, and ε is strain;

•Heat conduction equation (temperature sensing): ϱc∂t∂T=∇·(k∇T)+q, where ρ is density, c is specific heat capacity, k is thermal conductivity, and q is internal heat source intensity.

COMSOL Multiphysics is used to simulate and analyze the multi-physics field coupling effect. The spatial layout of sensitive units (staggered arrangement with spacing ≥200 μm) and signal frequency band division are optimized (temperature: 10~100 Hz, pressure: 1~10 kHz, vibration: 10~100 kHz, morphology: 1~10 MHz), and the crosstalk suppression ratio is increased to 45 dB. Multi-parameter synchronous collection is realized through FPGA 100 MHz global clock triggering, with a synchronization error ≤5 μs.

2.2.2 Attention LSTM Algorithm Principle

The standard LSTM hidden layer output is: ht=ot⊙tanh(ct), where ot=σ(Wo·[ht−1,xt]+bo) is the output gate, ct is the cell state, and ⊙ denotes the Hadamard product.

The improved LSTM incorporates an attention mechanism, with the core formula as follows:

$$\alpha t=\mathrm{softmax}(\mathrm{score}(ht,z1...zT))$$

$$context_t = \sum_{i=1}^{T} \alpha_t \cdot z_i$$

$$h_t{}' = \tanh(W_{context} \cdot [h_t{}, context_t] + b_{context})$$

Among them, α t is the attention weight (i=1T α t=1), $context_t$ is the context vector, zi is the 32 dimensional feature vector, and h_t is the improved output.

Algorithm convergence condition: When the learning rate η ≤ 0.01, the gradient norm of the loss function$||\nabla L|| \leq 10^{-3}$, and the number of iterations ≤ 500, convergence can be achieved. By using the Dropout mechanism (dropout rate=0.2) to prevent overfitting, the model trained on 100000 pieces of data (covering 5 typical industrial faults).

2.2.3 Weighted ICP Digital Twin Mapping Principle

The iterative update formula of the standard ICP algorithm is: T_{k+1}=argminT$\sum_{i=1}^{N}$wi(V_c,f_f)·$||p_i$−T(q_i)$||^2$, where pi is the target point cloud, qi is the source point cloud, and T is the rigid body transformation matrix.

Introducing process parameter weighting function to improve ICP algorithm:

$$T_{k+1} = \text{argmin}_T \sum_{i=1}^{N} w_i(v_c, f_f) \cdot ||p_i - T(q_i)||^2$$

$$w_i(v_c, f_f) = 0.4 \cdot (v_c/v_{ref}) + 0.3 \cdot (f_f/f_{ref}) + 0.3 \cdot d_i^2$$

Among them, vc is the cutting speed, ff is the feed rate, di is the distance from the i-th feature point to the center of gravity, V_{ref}=300 m/min} (reference cutting speed), f_{ref}=0.1m/r} (reference feed rate).

Convergence theorem: If the weight function satisfies 0<wi ≤ 1, then the iterative sequence Tk converges to the optimal transformation T∗.

Proof: Assuming the objective function J(T)=$\sum_{i=1}^{N}$ wi·||pi−T(qi)||2. Since wi>0 and ||pi−T(qi)$||^2$≥0, J(T) is a non negative convex function with a unique minimum value. Each iteration updates Tk using the least squares method, so that JTk+1<JTk. Therefore, the sequence Tk monotonically decreases with a lower bound and converges to the optimal solution T *.

The registration error is defined as the target registration error (TRE): TRE=mean((pi−Ttrue(qi))2)≤1.8μm.

3. Implementation of Core Technologies in the Integrated System

3.1 Design of Multi-Parameter Composite Sensing Module

3.1.1 Hardware Structure Design

The module adopts a "sandwich" integrated architecture (Figure 2) with an overall size of 1.5 cm×1.0 cm×1.0 cm (volume 1.5 cm^3), which is 70% smaller than traditional discrete solutions:

- Top layer: Miniature spectral confocal morphology sensing unit, equipped with multi-wavelength LED light sources (405 nm/532 nm/635 nm), spot size ≤6 μm, optical system focal length 8 mm, volume ≤0.5 cm^3;
- Middle layer: Temperature-pressure-vibration integrated unit, manufactured based on MEMS technology, with a minimum sensitive unit size of 0.1×0.1 mm and a sensing density of 400 points/cm^2. Encapsulation is realized through silicon-glass bonding technology, with a crosstalk suppression ratio ≥45 dB;
- Bottom layer: Signal conditioning circuit and FPGA control unit, integrated with a 24-bit AD converter (ADS1256) with a sampling rate of 100 SPS/channel. The FPGA model is Xilinx Artix-7 XC7A35T, responsible for synchronous control and data preprocessing.

The package adopts AlN ceramic material (thermal conductivity ≥170 W/(m·K)) with high temperature resistance and low thermal conductivity characteristics; humidity protection is realized through a PTFE waterproof and breathable membrane with an air permeability ≥1000 cm^3/(cm^2·24h), and an error rate ≤3% in a 95%RH (no condensation) environment (Chen W. & Liu J., 2023).

3.1.2 Performance Test Results

Three repeated tests were conducted under standard environment (25℃, 50%RH) and extreme working conditions, with the results shown in the following table:

Table 2. Performance Index Test Results of the Multi-parameter Composite Sensing Module

Sensing Parameter	Range	Standard Environment Accuracy	Response Time	Extreme Working Condition Test Environment	Extreme Working Condition Precision Attenuation	Test Method
Temperature	-40℃~150℃	±0.1℃	8 ms	-40℃ low temperature/150℃ high temperature/95%RH high humidity	≤3%	High-precision constant temperature chamber (Binder MK53) + standard thermometer calibration
Pressure	0~10 MPa	0.001%FS	1 ms	150℃ high temperature + 95%RH high humidity	≤2%	Pressure calibration platform (FUTEK LCM200) + pressure standard
Vibration	20 Hz~1 MHz	±0.5%FS	0.5 ms	1000 V/m strong electromagnetic interference	≤3%	Vibration table (Brüel & Kjær 4808) + standard accelerometer
Morphology	0~5 mm	±0.006 μm	50 μs	-40℃ low temperature/150℃ high temperature	≤2.5%	Laser interferometer (Zygo GPI XP) calibration
Synchronous Collection Error	-	-	≤5 μs	Full working conditions	≤8 μs	Oscilloscope (Tektronix MDO3024) synchronous trigger test

Test results show that the module can maintain high measurement accuracy under extreme working conditions, meeting the complex environmental usage requirements of the precision manufacturing industry.

3.2 Implementation of Edge Intelligent Algorithm Engine

3.2.1 Algorithm Flow and Optimization

The edge intelligent algorithm is implemented based on the STM32H743IGT6 MCU, with the core flow as follows:

Data collection: Synchronously receive multi-parameter sensing data through the SPI interface with a transmission rate of 50 Mbps and a sampling rate of 100 SPS;

Denoising processing: An improved wavelet threshold denoising algorithm is adopted, with an adaptive threshold $\lambda = \sigma\sqrt{2\ln N}$ (N is the data length). The signal-to-noise ratio is increased from 32 dB to 45 dB, and the data distortion rate is <1%;

Feature extraction: Perform FFT transformation on vibration signals to extract 5 characteristic frequencies (10 Hz/50 Hz/100 Hz/500 Hz/1 kHz), and construct a 32-dimensional feature vector combined with temperature and pressure data. Feature extraction time ≤80 μs;

Fault prediction: Improved LSTM model (input layer 32-dimensional → hidden layer 64-dimensional → attention layer → output layer 1-dimensional), outputting the equipment health index (0~1). The model training iteration number is 500, and the convergence error ≤0.001;

Control decision: The fuzzy PID algorithm dynamically adjusts parameters ($K_p \in [0,20]$, $K_i \in [0,1]$, $K_d \in [0,5]$), and the decision generation time ≤50 μs.

3.2.2 Algorithm Performance Verification

In the machine tool wear prediction scenario, 100 sets of measured data (including 5 types of typical fault types) are used to verify the algorithm, with the results shown in the following table:

Table 3. Edge Intelligent Algorithm Performance Index Verification Results

Evaluation Index	Test Result	Improvement Compared with Standard LSTM	Statistical Significance (P-value)
Fault Early Warning Accuracy	94.7%	31.3%	<0.001
Early Warning Lead Time	32.6 h	112%	<0.01
Inference Time	187 μs	-	<0.001
Model Overfitting Rate	2.3%	78.5%	<0.01

Verification results show that the improved edge intelligent algorithm is significantly superior to the standard LSTM algorithm in terms of early warning accuracy, response speed, and stability, and has industrial application feasibility.

3.3 Design of Cross-Protocol Interconnection Interface

3.3.1 Hardware and Software Implementation

The interconnection interface module uses the Xilinx Artix-7 FPGA as the core controller, integrating a Gigabit Ethernet PHY chip (DP83848), a CAN FD controller (TJA1057), and a LoRa module (SX1278), supporting wired and wireless dual-mode transmission with a hardware delay ≤5 μs (Chen W. & Liu J., 2023).

At the software level, a protocol conversion middleware is developed, realizing automatic protocol identification (recognition accuracy 100%), data parsing, and format conversion based on a state machine model with a conversion delay ≤10 μs; the AES-256 encryption algorithm is integrated with a key update cycle of 24 hours, and data transmission security complies with the ISO 27001 standard; time synchronization adopts the IEEE 1588 PTP protocol, realizing distributed clock synchronization through hardware timestamps with a synchronization accuracy of 100 ns.

3.3.2 Interconnection Performance Test

In an industrial-grade electromagnetic compatibility laboratory (electromagnetic interference intensity 1000 V/m), the transmission performance of different protocols is tested, with the results shown in the following table:

Table 4. Cross-protocol Interconnection Interface Performance Index Test Results

Communication Protocol	Transmission Rate	End-to-end Delay	Clock Synchronization Accuracy	Data Interaction Rate	Packet Loss Rate
PROFINET	1 Gbps	8 μs	100 ns	98.7%	0.1%
Ether CAT	100 Mbps	5 μs	50 ns	99.2%	0.05%
Modbus TCP	100 Mbps	12 μs	200 ns	97.8%	0.2%
LoRa (Wireless)	50 kbps	50 ms	1 ms	95.3%	0.5%

4. Experimental Verification and Result Analysis

4.1 Experimental Platform and Conditions

Experimental platforms for three scenarios:

semiconductor packaging (DISCO DFD6361 cutting machine), aero-engine manufacturing (DMG MORI DMU 50 machining center), and optical component processing (Nanotech 250UPL lathe). Control group: Single-parameter sensor combination (cost $4000, volume 15 cm^3). Experimental environment: Temperature 25±2℃, humidity 50±5%RH, vibration <0.1 g.

4.2 Experimental Results and Analysis

4.2.1 Semiconductor Packaging Experiment

Table 5. Wafer Thickness Detection Results (n=1000)

Scheme	Standard Deviation (μm)	Detection Efficiency (Wafers/Hour)	Cost (US Dollars)
Control Group	0.012	60	4000
Experimental Group	0.004	105	3200
Improvement Amplitude	66.7%	75.0%	-20%

Analysis of variance: $F=360.0$, $P<0.001$, $\eta^2=0.265$. Ablation experiments show that multi-parameter integration contributes 50%, edge algorithm contributes 25%, and PID control contributes 25%.

4.2.2 Aero-Engine Manufacturing Experiment

The turbine disk profile error is reduced from 8.7 μm to 4.2 μm (an increase of 51.7%), the surface roughness is reduced from 1.2 nm to 0.45 nm (an increase of 62.5%), and the processing cycle is shortened by 28.0%. The unplanned equipment downtime is reduced from 8.2% to 2.1%.

4.2.3 Optical Component Processing Experiment

The aspheric lens surface shape error is reduced from 0.032 μm to 0.015 μm (an increase of 53.1%), and the defect rate is reduced from 3.2% to 0.5% (an increase of 84.4%).

4.2.4 Failure Cases and Long-term Stability

Failure case analysis: 3 typical faults are caused by sensor installation deviation (2 cases) and extreme electromagnetic interference (1 case), which have been solved by optimizing the installation process and shielding design. Six-month long-term stability test: Precision attenuation ≤1.2%, mean time between failures >5000 hours.

4.3 Comprehensive Benefit Analysis

The average machining accuracy is increased by 57.2%, production efficiency is increased by 47.7%, and manufacturing costs are reduced by 21.2%. The effect varies in different scenarios: semiconductor packaging efficiency is significantly improved (75%), while aero-engine manufacturing is limited by process complexity with an improvement of 28%.

5. Comparative Analysis with Existing Technologies

Table 6. Technical Comparative Analysis

Technical Scheme	Sensing Parameters	Measurement Accuracy	Response Delay	Volume (cm^3)	Cost (US Dollars)	Publication Year
MIT Composite Sensing (Rus D, et al., 2023)	2	±0.01 μm	5 ms	>5	5000	2023
Stanford AI Sensing (Zhang Y, et al., 2024)	3	±0.008 μm	50 ms	>3	4500	2024
Commercial Single-parameter Combination	4 (Discrete)	±0.025 μm	>100 ms	15	4000	-
Integrated System in This Paper	4 (Integrated)	±0.006 μm	0.8 ms	1.5	3200	-

Note: Due to the lack of open-source implementations, direct comparison under identical conditions was not feasible.

6. Conclusions and Prospects

6.1 Research Conclusions

This paper constructs a four-layer integrated system, develops a four-parameter MEMS sensing module, an attention LSTM algorithm, a cross-protocol middleware, and a weighted ICP mapping algorithm. Verification through three industrial scenarios realizes the collaborative optimization of accuracy, efficiency, and cost, solving the core technical bottlenecks of the precision manufacturing industry.

6.2 Research Limitations and Future Directions

Limitations: Wireless transmission distance ≤3 km, and the recognition rate of niche faults is less than 85%. Future directions: (1) Adopt 5G industrial modules to expand transmission distance; (2) Integrate Transformer to improve fault recognition rate; (3) Optimize the digital twin update efficiency to ≥200 Hz; (4) Promote technical standardization.

References

Besl P J, et al. (1992). A method for registration of 3-D shapes. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 14*(2), 239-256.

Chen W, Liu J. (2023). Sensing Technology in Smart Manufacturing. *IEEE Transactions on Industrial Electronics, 70*(5), 5234-5246.

Deloitte. (2024). 2024 High-End Manufacturing Technology White Paper.

Grand View Research. (2024). Industrial Robotics Market Size Report, 2024.

Kim B, et al. (2023). Reinforcement learning for robotic assembly. *IEEE Transactions on Robotics, 39*(2), 1123-1138.

Liu C, et al. (2024). Smart Manufacturing based on Sensing Technology. *Sensors, 24*(19), 5872.

Liu J, et al. (2024). Multi-sensor Fusion Technology in Precision Manufacturing. *Journal of Mechanical Engineering, 60*(12), 178-192.

Pomeas. (2024). Spectral Confocal Displacement Sensor.

Rus D, et al. (2023). Multi-parameter integrated sensors. *Science Robotics, 8*(78), eaad2896.

Schmidt M, et al. (2019). Force-torque sensing in robotic manipulation. *Robotics and Autonomous Systems, 117*, 103322.

Zhang Y, et al. (2024). AI-driven sensing optimization. *Journal of Manufacturing Science and Engineering, 146*(3), 031005.