

Phase 3: Implementation of Project

Title: AL-EBPL-Structural Health Monitoring

Objective

The goal of Phase 3 is to implement the core components of the AL-EBPL-Structural Health Monitoring system, based on the designs and innovative strategies developed during Phase 2. This includes the development of sensor networks, data acquisition systems, basic AI analytics for anomaly detection, and the application of data security protocols.

1. Sensor Network Deployment

Overview

The backbone of the structural health monitoring system is its sensor network, which captures real-time data on structural performance and integrity.

Implementation

- Sensor Types: Vibration sensors, strain gauges, and accelerometers are deployed on key structural points.
- Data Acquisition: Sensors feed into an embedded system capable of logging and transmitting data wirelessly or via local storage.
- Calibration: Sensors are calibrated to ensure accuracy and reliability in measurement.

Outcome

A network of functional, calibrated sensors capable of real-time structural data capture.

2. AI Model for Anomaly Detection

Overview

AI is employed to analyze sensor data and identify anomalies that may indicate structural damage or degradation.

Implementation

- Model Type: A lightweight machine learning model is trained using baseline sensor data from healthy structural conditions.
- Functionality: The model flags deviations from baseline behavior (e.g., abnormal strain or vibration patterns).
- Training Data: Simulated and recorded structural response data under varying loads.

Outcome

An AI model capable of basic anomaly detection to flag potential issues in the structure.

3. Edge Device and Cloud Integration (Optional)

Overview

Integration with edge computing devices and cloud platforms is optional in Phase 3 but foundational frameworks will be laid.

Implementation

- Data Transfer: Establish basic protocols for transmitting data from the structure to the cloud.
- Edge Processing: Use of microcontrollers or embedded systems to preprocess data before transmission.
- Cloud Storage: Initial setup of cloud databases to store historical monitoring data.

Outcome

System can optionally send and archive sensor data for remote access and further analysis.

4. Data Security Implementation

Overview

Due to the sensitive nature of structural safety data, appropriate data protection mechanisms are essential.

Implementation

- Encryption: Sensor data is encrypted during transmission and storage.
- Access Control: Only authorized personnel can view or manipulate data.
- Secure Logging: All data transactions are logged for traceability.

Outcome

Secure infrastructure in place for handling monitoring data, meeting basic cybersecurity standards.

5. Testing and Feedback Collection

Overview

Initial testing of the monitoring system is carried out to evaluate accuracy, response time, and reliability.

Implementation - Pilot Deployment: A controlled environment or small-scale structure is monitored to simulate real-world scenarios. - Validation: Sensor data is compared against expected structural responses. - Feedback: Engineers and stakeholders provide feedback for improvements.

Outcome

A functional prototype system is validated, and feedback is collected for refining the system in the next phase.

Challenges and Solutions

1. Data Noise

- Challenge: Environmental interference can introduce noise into sensor data.
- Solution: Implement digital filtering and data preprocessing techniques.

2. Sensor Drift

- Challenge: Long-term monitoring may be affected by sensor drift.
- Solution: Regular recalibration and algorithmic drift correction.

3. Limited Connectivity

- Challenge: Remote sites may have poor data transmission capabilities.
- Solution: Edge processing and data batching for delayed upload.

Outcomes of Phase 3

- 1. Operational Sensor Network: Structural parameters are captured accurately in real-time.
- 2. AI Anomaly Detection: Basic AI models detect unusual structural behavior.
- 3. Optional Cloud Integration: Structural data can be transmitted and stored remotely.
- 4. Data Security: All data is encrypted and access-controlled.
- 5. Initial Testing: A small-scale deployment confirms feasibility and effectiveness.

Next Steps for Phase 4

- 1. AI Model Enhancement: Improve accuracy with more training data and advanced models.
- 2. System Scalability: Adapt system for monitoring larger or more complex structures.
- 3. Automated Alerts: Develop notification systems for structural risk thresholds.

SCREENSHOTS OF CODE and PROGRESS - MUST BE ADDED HERE FOR PHASE 3

program:

```
import numpy as np
import matplotlib.pyplot as plt

# Simulate vibration data for a healthy and a damaged structure
def simulate_vibration(frequency, noise_level=0.2, duration=5.0, sample_rate=1000):
    t = np.linspace(0, duration, int(sample_rate * duration), endpoint=False)
    signal = np.sin(2 * np.pi * frequency * t)
    noise = noise_level * np.random.randn(len(t))
    return t, signal + noise

# Simulate healthy structure (e.g., 10 Hz) and damaged one (e.g., 8 Hz)
t, healthy_signal = simulate_vibration(10)
_, damaged_signal = simulate_vibration(8)

# Perform FFT
def compute_fft(signal, sample_rate=1000):
    N = len(signal)
    freqs = np.fft.fftfreq(N, 1 / sample_rate)
    fft_values = np.abs(np.fft.fft(signal))
    return freqs[:N//2], fft_values[:N//2]

healthy_freqs, healthy_fft = compute_fft(healthy_signal)
damaged_freqs, damaged_fft = compute_fft(damaged_signal)

# Plot results
plt.figure(figsize=(12, 6))

plt.subplot(2, 1, 1)
plt.plot(t, healthy_signal, label='Healthy')
plt.plot(t, damaged_signal, label='Damaged', alpha=0.7)
plt.title('Simulated Vibration Signals')
plt.xlabel('Time (s)')
plt.ylabel('Amplitude')
plt.legend()

plt.subplot(2, 1, 2)
plt.plot(healthy_freqs, healthy_fft, label='Healthy FFT')
plt.plot(damaged_freqs, damaged_fft, label='Damaged FFT', alpha=0.7)
plt.title('Frequency Domain Comparison')
plt.xlabel('Frequency (Hz)')
plt.ylabel('Amplitude')
plt.legend()

plt.tight_layout()
plt.show()
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output:

