Report: Verifying Oscilloscope Hardware for 12-bit Resolution

The purpose of this project is to verify whether the oscilloscope hardware under evaluation genuinely supports a 12-bit vertical resolution. By analyzing and processing the raw data captured from the oscilloscope, we aim to assess its effective resolution and determine if it meets the stringent requirements of high-precision applications. Accurate data handling and thorough analysis are essential to ensure the oscilloscope's reliability and performance in industrial environments where precise measurements are critical.

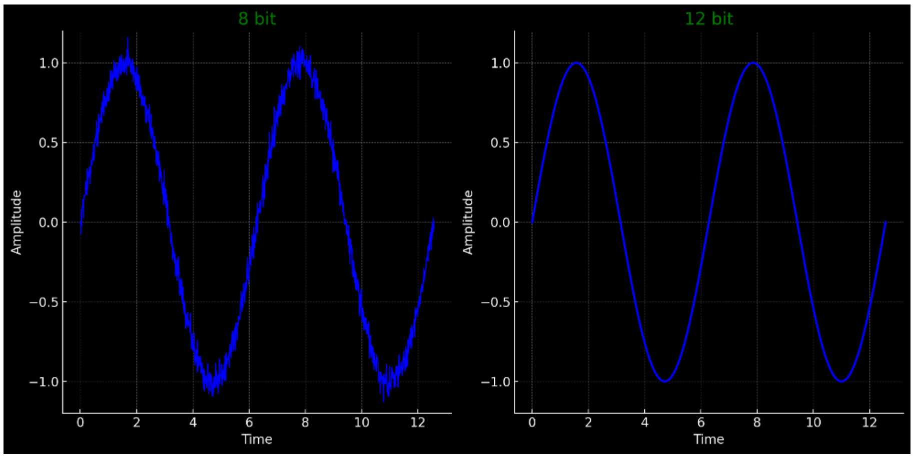


Figure 1. 8-bit vs. 12-bit resolution comparison

Oscilloscopes are indispensable tools in electronics for observing and measuring electrical signals. The vertical resolution of an oscilloscope determines its ability to detect and display small voltage differences, which is crucial in applications like high-speed data communications, medical instrumentation, and advanced research. In this project, we analyzed a dataset containing **100,000 data points** of a sine wave captured by the oscilloscope hardware. The sine wave encompasses **100 cycles**, providing a comprehensive dataset for evaluation. The primary goal is to determine whether the oscilloscope hardware provides a true 12-bit resolution, corresponding to **4,096 unique quantization levels** ranging from 0 to $2^{12}-1$ (0 to 4095 in decimal or 000 to FFF in hexadecimal).

Methodology | 方法

1. Data Acquisition

The oscilloscope was configured to capture a high-fidelity sine wave signal, ensuring the input fully utilized the vertical dynamic range. This setup is essential for accurately evaluating the oscilloscope's 12-bit resolution capabilities. The signal was exported as raw numerical data for further analysis using the Fast Fourier Transform (FFT), a method that converts a time-domain signal into its frequency-domain representation. The FFT computation was performed using the **NumPy** library (numpy.fft), which is a widely used Python package for numerical and scientific computing. As shown in Figure 2, the original signal was decomposed into its top 5 sine wave components, highlighting their frequency, amplitude, and phase. The report also includes detailed testing conducted on one of these sine wave samples.

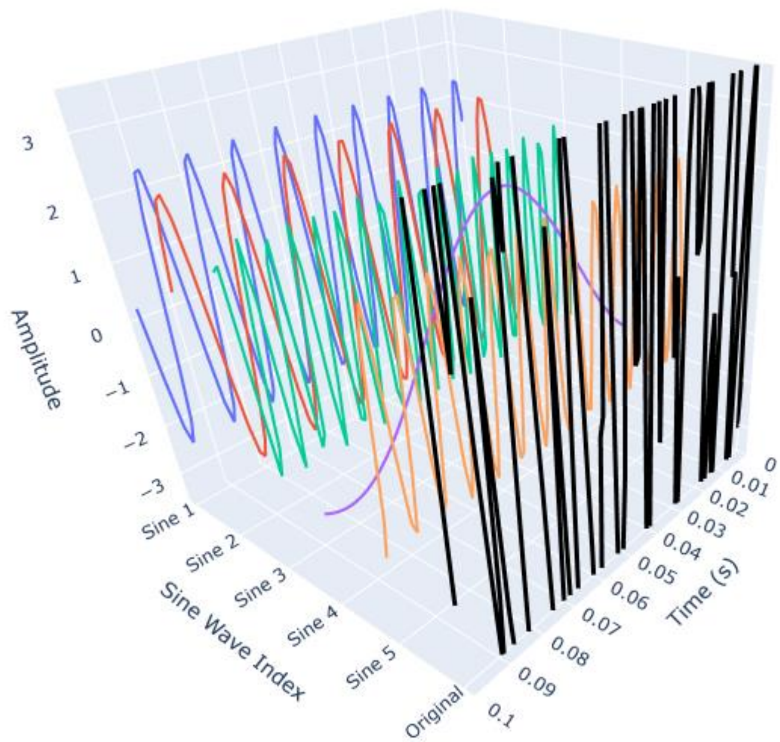


Figure 2. 3D Representation of FFT-Based Signal Decomposition into Top 5 Components

2. Frequency Analysis Using FFT and PCA| 使用 FFT 和 PCA 进行频率分析

To verify the effective resolution and frequency content captured by the oscilloscope, we performed a frequency analysis using the **Fast Fourier Transform (FFT)** and **Principal Component Analysis (PCA)**. This approach allowed us to identify and quantify the dominant frequency components present in the signal and assess the oscilloscope's ability to capture detailed frequency information.

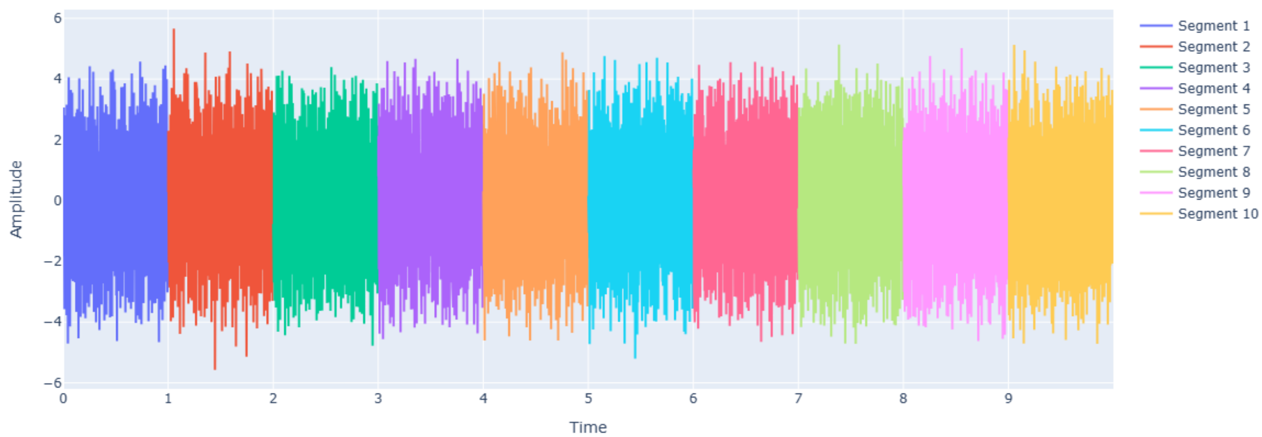
a. Fast Fourier Transform (FFT)

The FFT converts the time-domain signal into its frequency-domain representation, enabling us to analyze the frequency components within the signal.

Process:

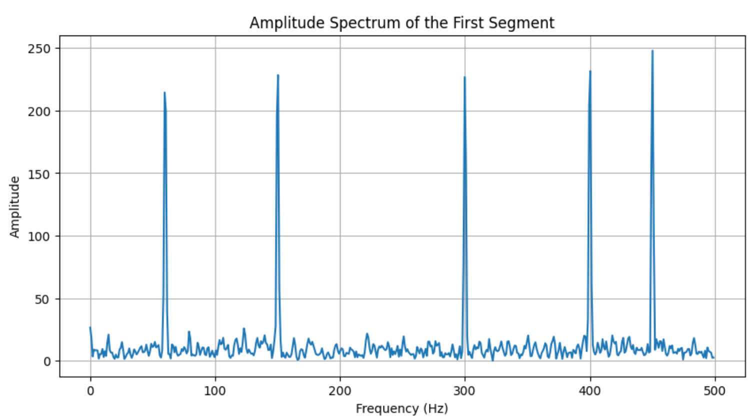
1. **Signal Segmentation:**

- The captured signal, consisting of 100,000 data points, was divided into **10 equal-length segments**.



- Segmenting the signal provides multiple observations, which is essential for effective statistical analysis and improves the reliability of subsequent PCA.

2. **FFT Computation:**
    - For each segment, the FFT was computed to transform the time-domain data into the frequency domain.
    - We used an FFT size (N_{FFT}) of 1024 points for all segments.
        - **Zero-Padding:** If the segment length was shorter than N_{FFT}, zeros were added to extend the segment length. This increases the frequency resolution of the FFT without altering the original signal content.
    - The result is a set of **magnitude spectra**, each representing the amplitude of frequency components within that segment.



3. **Frequency Bins:**
    - The FFT output provides a set of frequency bins, each corresponding to a specific frequency.

b. Principal Component Analysis (PCA)

PCA was applied to the frequency-domain data to identify the most significant frequency components contributing to the signal's variance.

Why Use PCA:

- **Dimensionality Reduction:** The FFT produces many frequency bins (features). PCA reduces this high-dimensional data into a smaller set of uncorrelated variables called principal components.
- **Pattern Identification:** PCA helps to identify patterns in the data by focusing on the directions (principal components) that capture the most variance.

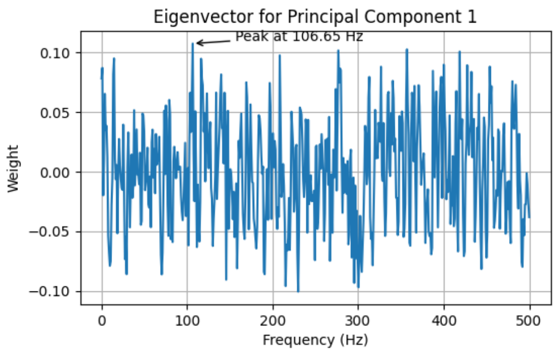
What PCA Represents:

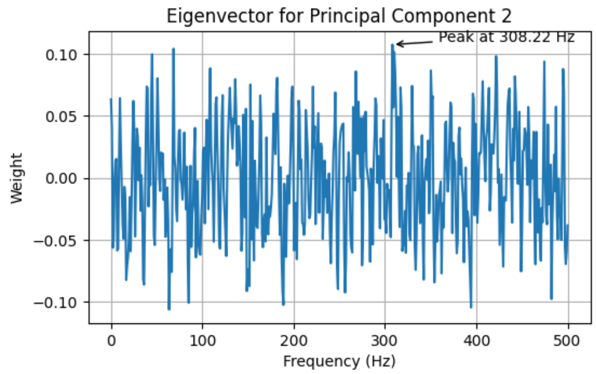
- **Principal Components:** Each principal component is a linear combination of the original frequency bins and represents a direction in the feature space along which the data varies the most.
- **Eigenvectors and Eigenvalues:**
    - **Eigenvectors:** Represent the directions (frequency combinations) of maximum variance (principal components).
    - **Eigenvalues:** Indicate the amount of variance captured by each principal component.

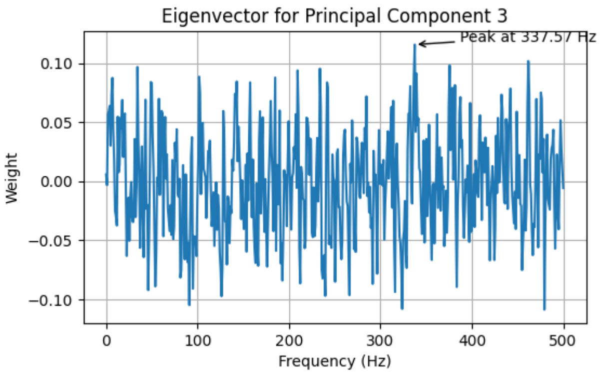
Process:

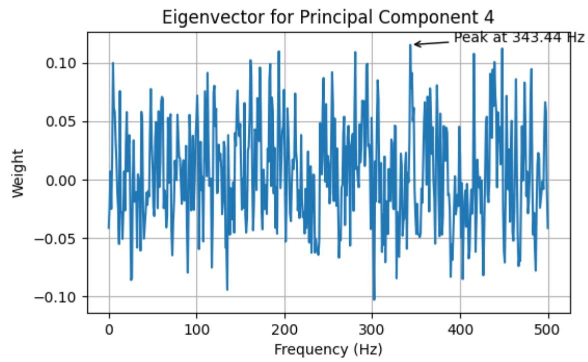
1. **Data Matrix Construction:**
    - The magnitude spectra from the FFT of each segment were organized into a **data matrix** X.
        - **Rows (N)**: Each row corresponds to a segment.
        - **Columns (M)**: Each column corresponds to a frequency bin from the FFT.
2. **Standardization:**
    - The data matrix was standardized to have **zero mean** and **unit variance** across each frequency bin.
    - **Purpose:** Standardization ensures that all frequency bins contribute equally to the PCA, preventing bias due to differing scales.
3. **PCA Computation:**
    - PCA was performed on the standardized data matrix X_{std}.
    - **Computation Steps:**
        - Calculate the covariance matrix of X_{std}, called it C
        - Compute the eigenvalues and eigenvectors of the covariance matrix C.
        - Sort the principal components based on the eigenvalues in descending order.
4. **Selection of Top Frequencies:**

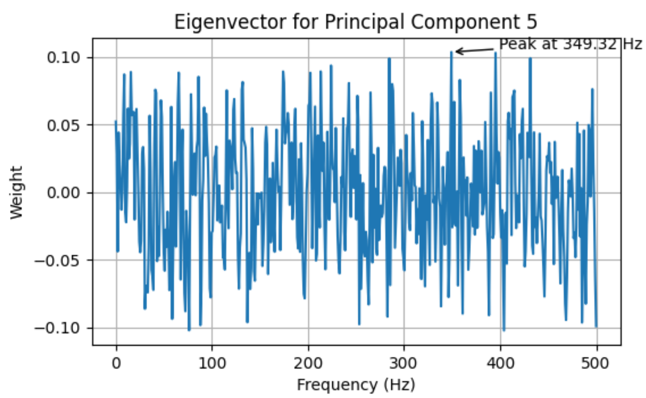
- We analyzed the **top five principal components** that explained the most variance in the data.
- **Identifying Dominant Frequencies:**
    - For each principal component (eigenvector), we identified the frequency bin with the highest absolute value (loading).
    - The frequency bins with the highest loadings are the ones that contribute most to that principal component.
    - By mapping these frequency bins back to actual frequency values, we identified the dominant frequencies in the signal.











Dominant Frequencies:

- These frequencies correspond to the peaks in the principal components' eigenvectors.
    - Frequency 1: 106.65 Hz
    - Frequency 2: 308.22 Hz
    - Frequency 3: 337.57 Hz
    - Frequency 4: 343.44 Hz
    - Frequency 5: 349.32 Hz
- The high loadings at these frequencies indicate they are the most significant contributors to the signal's variance.

3. 数据转换 & 覆盖范围分析 | Data Conversion & Coverage Analysis

Hexadecimal representation offers a concise and human-readable format for binary data. Each hexadecimal digit represents four binary bits, simplifying the visualization and analysis of high-resolution data.

Data Processing Steps:

- **Conversion to Hexadecimal:** Each raw data point was converted to its corresponding hexadecimal value using Python scripts. This step ensures that the data is in a standardized format for bit-level analysis.

```
def convert_to_hex(num):
    if num < 0:
        return hex((1 << 32) + num)[2:]
    else:
        return format(num, '04x')
```

- **Extraction of Relevant Bits:** To focus on the 12-bit resolution, the 12 least significant bits (LSBs) were extracted from each data point. This extraction isolates the portion of the data that directly corresponds to the oscilloscope's vertical resolution.

```
def extract_12_bits(hex_str):
    binary_str = bin(int(hex_str, 16))[2:].zfill(16)
    return binary_str[-12:]
```

- **Conversion to Binary Representation:** The extracted 12-bit data was converted to binary format for detailed bit-level analysis, enabling us to inspect the distribution and utilization of the quantization levels.

A thorough analysis was conducted to determine whether all possible 12-bit values are represented in the dataset, which is essential for verifying the oscilloscope's true resolution.

- **Generation of All Possible Values:** We generated a complete list of all possible 12-bit hexadecimal values from 000 to FFF, totaling 4,096 possible values.
- **Identification of Unique Values:** Unique 12-bit values present in the captured data were extracted to assess the coverage.
- **Detection of Missing Values:** By comparing the complete list of possible values with the unique values from the dataset, we identified which quantization levels were not utilized.

Results | 结果

The analysis revealed that the oscilloscope did not utilize the full range of 12-bit values in the captured data:

- **Total Possible Quantization Levels:** 4,096
- **Unique Quantization Levels Observed: 3,005**
- **Missing Quantization Levels: 1,091**, indicating gaps in the resolution.

Implications for Precision Measurements

The absence of 1,091 quantization levels suggests limitations in the oscilloscope's ability to resolve fine signal details. In high-precision applications, this could lead to measurement inaccuracies and a failure to detect subtle signal variations essential for accurate diagnostics and analysis.

Recommendation to Increase Sample Size

To address the gaps identified in the quantization levels, it is recommended to increase the sample size from **100,000** to **500,000** data points. By increasing the sample size:

- **Improved Data Resolution:** A higher number of samples increases the likelihood of covering all possible quantization levels, enhancing the oscilloscope's effective resolution.
- **Enhanced Signal Representation:** Capturing more data points allows for a more detailed representation of the signal, improving the ability to detect subtle changes.
- **Statistical Reliability:** A larger dataset provides better statistical significance, reducing the impact of anomalies and improving the overall accuracy of the analysis.

Reference | 引用

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