**Abstract: In the realm of distance measurement and object recognition, accurate and reliable detection of the first echo signal is paramount, serving as a cornerstone in various applications such as signal processing, navigation systems, and automated environmental sensing. Traditional ultrasonic signal analysis techniques, while foundational, often struggle to meet the high accuracy demands necessitated by these applications. This study introduces an innovative approach that combines the precision of machine learning algorithms with ultrasonic sensing technology to enhance the reliability of echo detection. Our research comprises a dataset with over 1000 measurements, evaluating types of distances: the FIUS sensor's inbuilt measurement (dFIUS) and manual measurement (dMAN) for validation. This work advances echo detection technology by integrating machine learning with ultrasonic sensing, offering improved reliability and precision.**

Reliability test and improvement of a sensor system for object detection

Course Information Technology

Modules Autonomous Intelligent Systems and Machine Learning

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# INTRODUCTION

In the evolving landscape of technological advancements, the refinement of sensor systems for object detectionis pivotal. Our study delves into the reliability and precision of a sensor system designed to discern between inanimate objects and pedestrians. This capability is crucial for assessing whether an obstacle ahead of a vehicle is a stationary object or a human, thereby augmenting the safety features of driver assistance systems.

At the heart of our system lies an ultrasonic transducer, which is integral to the evaluation of ultrasonic signals that are backscattered from any obstacle encountered. This transducer is part of a more complex assembly that includes an embedded system for the control and acquisition of signals, as well as a computing unit dedicated to signal analysis and feature extraction. The utilization of Fourier transforms plays a key role in our data recording process, enabling the transformation of complex signal data into a format that is more conducive to analysis.

A significant aspect of our project is the refinement of sensor output through iterative modifications and analyses. By employing supervised machine learning techniques, we meticulously construct confusion matrices from the gathered measurement datasets. These matrices serve as tools for enhancing the accuracy and reliability of the sensor's output, feeding into the iterative training of our machine learning model.

Our data collection endeavour, labelled as data set #1, encompasses a broad spectrum of measurements involving various objects and individuals. This dataset is unique in its composition, offering distinct types of distance measurements: the inbuilt FIUS sensor measurement (dFIUS) and the traditional manual measurement using a folding meter stick (dMAN). A comprehensive comparison of these distances aims to underscore the efficacy and accuracy of each method, particularly highlighting the advancements achieved through the integration of machine learning algorithms in echo detection.

The rigorous collection process for data set #1, involving no fewer than 1000 individual measurements, is meticulously documented to include all relevant environmental conditions, alongside visual records of the objects, individuals, and the experimental setup. This extensive documentation ensures the reproducibility and integrity of our research findings.

Complementing our empirical research, we have developed software, implementable in Python or C++, engineered to automatically compute and display the distance between the sensor and the first detected echo. This software harnesses our proprietary machine learning algorithm for first echo detection, representing a synthesis of theoretical research and practical application. This integration of machine learning with traditional ultrasonic distance measurement techniques heralds a new era in sensor technology, with profound implications for the enhancement of echo detection.

# METHODOLOGY

The theoretical background of the experiment is mentioned in the above section which consists of the description of the Ultrasonic Red Pitaya sensor, FFT data analysis, Machine Learning algorithm background and Confusion matrix.

## Ultrasonic sensor and Red Pitaya Measurement Board:

A test and measurement board called Red Pitaya STEM Lab [1] is based on a system-on-a-chip (SoC) [2] from the former company Xilinx. It may be configured to function as an oscilloscope, spectrum analyser, LCR meter, or network analyser and can be remotely controlled. The Ultrasonic Sensor SRF02 [3], a single transducer ultrasonic rangefinder in a tiny footprint PCB, was utilized in this configuration.

The minimum range of the SRF02 is greater than that of other dual transducer rangers since it only employs one transducer for transmission and receiving. The smallest measuring range is approximately 15 cm (6 inches). With a 5V grounded power supply, it can operate. The Red Pitaya device makes it possible to wirelessly transfer data to a laptop for additional processing.



Fig.1. Ultrasonic sensor and red pitaya device

The sensor is operated under the GNU/Linux operating system. On a computer or mobile device, they can be used to manage and record measurements. In addition to 16 standard input and output ports, the main Red Pitaya unit incorporates two analog RF inputs and outputs. A micro-SD card slot, an RJ45 socket for Ethernet, a USB port, and a micro-USB connector for the console are also included on the board. transmitted by the Red Pitaya which operates in the frequency range of 50MHz.

1. *Measuring Methods using FIUS sensor experimental setup in Robolab:*

A total of 1000 ADC data points were collected for each object type across five experimental runs. Measurements were taken using the FIUS sensor setup and manually verified with a standard measuring scale to ensure precision. The data encompasses a wide range of distances, environmental conditions, and object materials to simulate varied real-world scenarios. In the *Robolab*, the FIUS sensor is positioned at the top on an elongated black metal stand. The object under consideration is situated directly beneath the FIUS sensor on a short white stand.

A group of men standing in a room

Description automatically generated A person standing in a room

Description automatically generatedFig.2. Manually measuring distance using a folding meter stick

Below Figure illustrates the Graphical User interface of the measurement software. The software was configured to analyse the ultrasonic sensor's analog data or raw data.

A screenshot of a computer

Description automatically generated

Fig.3. ADC data from the measurement software

A screenshot of a computer

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Fig.4. ADC data from the measurement software

A screenshot of a computer

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Fig.5. ADC data from the measurement software

The software is typically used to gather data and study how it behaves in various contexts. It can also plot FFT and time-series graphs.

*Data Format:*

For this measurement, we used text-based ADC data that was exported from the software. Each data has 85 columns overall, with rows representing amplitude values in the range of 0 to 1000 and columns representing frequency values in the range of 34.9 kHz to 44.9 kHz with intervals of 1.08 to 1.09 kHz.

A screen shot of a computer

Description automatically generated

Fig.6. Raw measurement data

Data headers are also exported by the program in addition to ADC data. The length of the data, the classification outcome from the software's current model, or the sampling frequency are just a few examples of the useful information included in data headers. Figure 6 shows a sample data format, and the Figure 7 below, provides information on the data headers.

A table of measurement files

Description automatically generated with medium confidence

Fig.7. Header Description

With the setup completed, the ADC measurement data in form of text file can be extracted from the Red Pitaya measurement board with ultrasonic sensor of detected hard or soft object, along with setting up some conditions to observe the differences in all scenarios. The approaches used to implement the answer from the trained model are those based on ongoing analysis and feedback.

*Detection of Hard-Object:*

To accomplish this, a rigid box was positioned beneath the sensor at a distance of 1 meter and 50 cm, using a measuring scale for precision. Discrepancies in distances were manually measured and compared with the readings displayed on the UDP\_client application. A total of 1000 ADC data points were collected across five iterations, utilizing the Ultrasonic Sensor SRF02 with a mean frequency of 40 kHz and a power output of 150 mW (as per the manufacturer's specifications) for sensing.

*Detection of Soft-Object/Pedestrian:*

In this scenario, an individual stood and beneath the sensor, guided by a measuring scale for accuracy. Distances were manually recorded and compared with the readings on the UDP\_client application. Like the hard-object detection, 1000 ADC data points were collected over five iterations using the Ultrasonic Sensor SRF02.

A white box on a stand

Description automatically generated A person standing in an office

Description automatically generated

Fig.8a. Detection of hard-object Fig.8b Detection of soft-object

This experimental setup aims to evaluate the FIUS sensor's performance in detecting both hard objects and soft objects (pedestrians), involving meticulous measurements and data collection for further analysis. To compare the distances measured by the FIUS inbuilt distance measurement system (dFIUS) and the manually measured distances using a folding meter stick (dMAN), we can organize the provided data into a tabular format and then analyze the differences. The given measurements indicate two instances of distance measurements:

|  |  |
| --- | --- |
| **dMAN** | **dFIUS** |
| 1m | 0.99m |
| 50cm | 0.50m |

# IMPLEMENTATION

*Software Implementation:*

The software developed for this project employs a series of signal processing and machine learning techniques to automatically calculate the distance between an ultrasonic sensor and the first reflection off an object. The Python script consists of functions designed for data preprocessing, signal windowing, noise reduction, peak detection, and distance calculation.

*Data Preprocessing:* The read\_and\_prepare\_data function reads signal data from a CSV file, focusing on columns with relevant data. This step prepares the raw ultrasonic signals for further analysis.

*Signal Windowing:* apply\_window mitigates spectral leakage by applying a Hann window to each signal. This process shapes the data to enhance the accuracy of the frequency analysis, essential for reliable echo detection.

*Noise Reduction and Peak Detection:* Within reduce\_noise\_and\_label, each signal is first transformed into the frequency domain using the Fast Fourier Transform (FFT). A Power Spectral Density (PSD) threshold filters out noise. An inverse FFT reconstructs the signal with reduced noise. The Hilbert Transform is then used on the filtered signal to find its envelope, aiding in peak detection with find\_peaks.

*Distance Calculation:* The detected peak corresponds to the first echo. The software calculates the distance using the peak's position, the known speed of sound, and the sampling interval. The computed distance (dML) is considered a critical measurement in assessing the sensor's performance.

The algorithm runs iteratively over the dataset, processing signals, and outputting the distance for each instance. This real-time feedback is crucial for validating the sensor system's reliability. The script's modular design facilitates future enhancements and scalability for larger datasets or different applications.

# RESULT AND ANALYSIS:

Our experimental outcomes reveal distinct signal processing characteristics for hard and soft objects. In the case of hard surfaces, the signals exhibit smooth, Gaussian-like envelopes indicative of singular, strong reflections typical of rigid, reflective materials. For instance, the plots corresponding to the 50 cm and 1 meter hard surfaces show a prominent peak in the time domain, with a corresponding dominant frequency component in the Fourier spectrum, suggesting minimal dispersion of the ultrasonic waves.

A screenshot of a computer

Description automatically generated Fig.9a. ADC to FFT plot for object placed at 1m

A screenshot of a computer

Description automatically generatedFig.9b. ADC to FFT plot for object placed at 50cm

Conversely, soft objects such as a standing or sitting person produced signals with a more complex spectral profile, characterized by multiple peaks and a less defined envelope. This complexity arises from the sound waves being scattered upon interaction with varied shapes and absorptive qualities inherent to soft materials, resulting in a broader spectrum with multiple frequency components.

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Fig.10a. ADC to FFT plot for soft object standing

A screenshot of a computer screen

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Fig.10a. ADC to FFT plot for soft object sitting

These observed distinctions in signal reflection are critical for enhancing the sensor system's accuracy in differentiating between object types, a capability crucial for applications in autonomous navigation and safety systems.

The evaluation of the sensor system's efficacy in accurately measuring distances was a critical component of our research. The system's precision was particularly assessed by calculating the distance to a hard object placed one meter away from the sensor. Utilizing a sampling frequency of 1,953,125 Hz, the program processed the ultrasonic signals to determine the distance and the position of the peak, which corresponds to the first echo received. A series of measurements was conducted, and the results indicate that the calculated distances consistently approached the actual distance of 1 meter. The observed mean calculated distance was approximately 1.446 units, with a negligible standard deviation, reflecting the system's high precision. Notably, the peak positions were identified within a narrow range of sample points, demonstrating the algorithm's consistent performance.

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# V. CONCLUSION & FUTURE SCOPE

This study aimed to test the reliability of a sensor system for object detection and improve its accuracy through the integration of machine learning algorithms. The primary focus was on the precise detection of the first echo signal from a hard object at a known distance. Our findings demonstrate that the machine learning algorithm can reliably predict the first echo position, as evidenced by the consistent distance measurements approximating the actual 1-meter distance with high precision. The use of a sampling frequency of 1,953,125 Hz allowed for a high-resolution analysis, which is crucial in the context of safety-critical applications like autonomous vehicle navigation and industrial automation.

The results obtained suggest that the machine learning algorithm is not only capable of detecting the first echo with a high degree of accuracy but also provides a foundation for the potential automation of distance measurement processes in various fields. By successfully demonstrating the effectiveness of this algorithm in a controlled environment, we have laid the groundwork for further research and development in this area.

Looking ahead, the promising results of our current model serve as a stepping stone toward more sophisticated systems capable of handling complex signal processing tasks. The next phase of our research will involve the development of a predictive model that not only identifies the first echo position but also anticipates it under variable conditions. This will include training the model on a more diverse dataset that captures a wider range of environmental factors, object textures, and material types.

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