Convolutional Neural Networks with Data Augmentation for Object Classification in Automotive Ultrasonic Sensing

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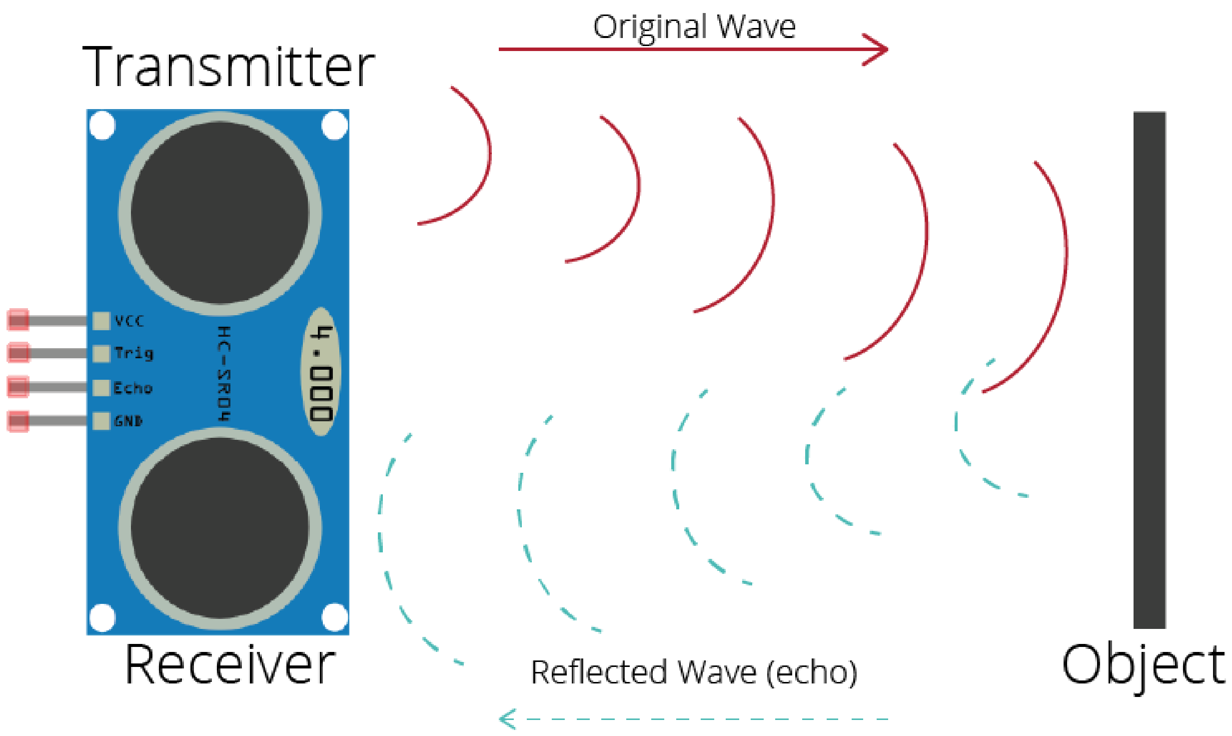
Outline

Introduction to Automotive Ultrasonic Sensing

What is an Ultrasonic Sensor and how it’s work ?

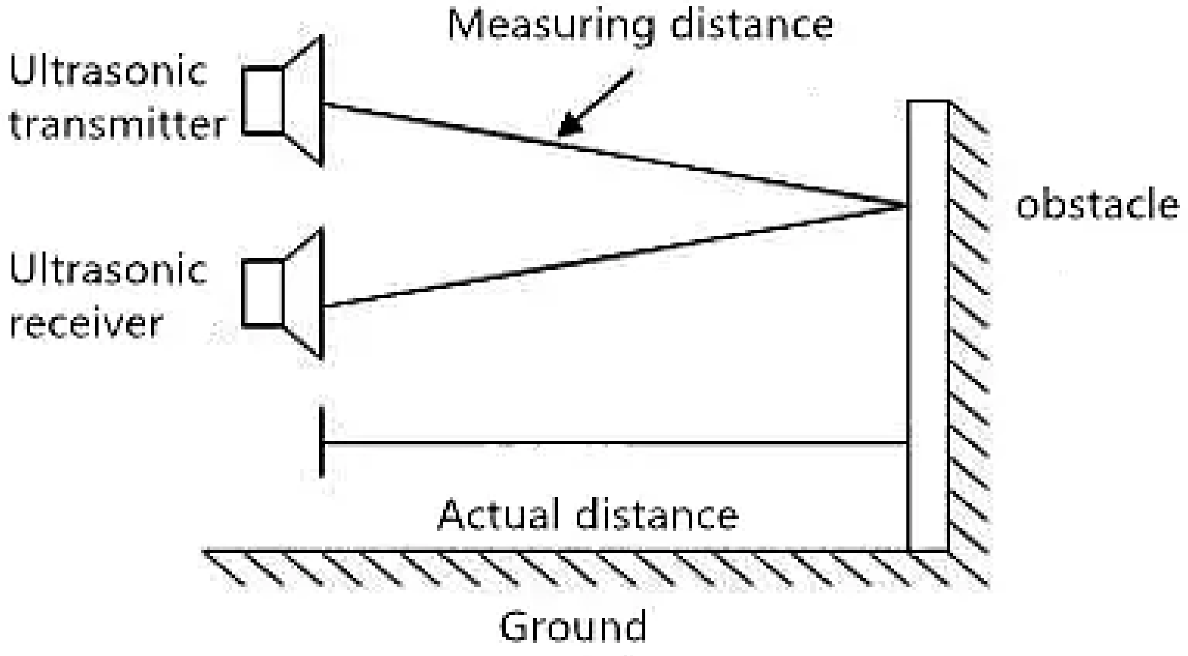


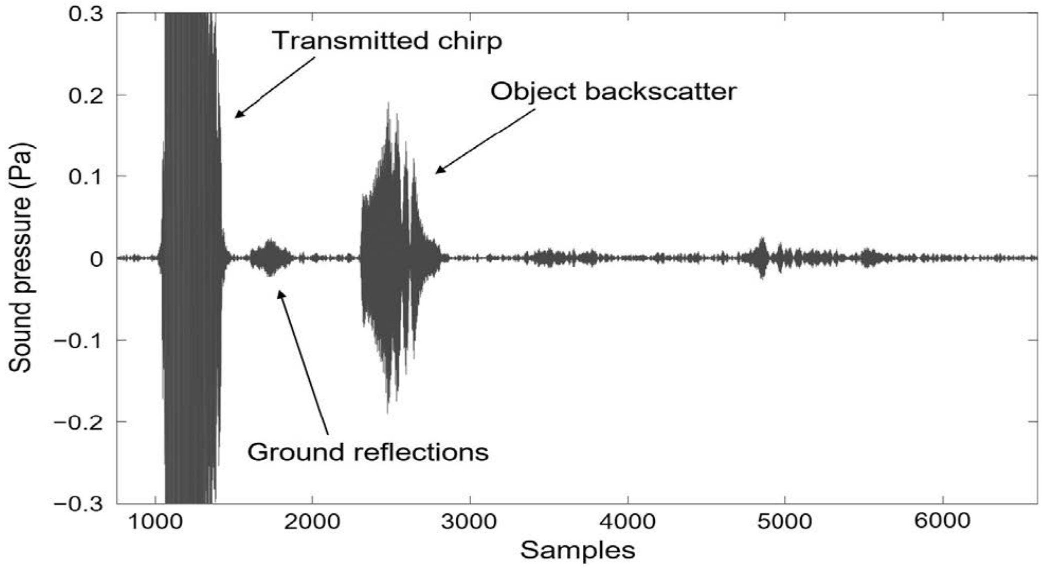
Why Ultrasonic Sensor ?

- Low-cost
- robust
- reliable sensor technology
- High Accuracy in Near-Field Detection
- Low Power Consumption

Introduction to Automotive Ultrasonic Sensing

How to calculate the distance to obstacles ?





Pulse-echo method

Time-of-Flight

$\boldsymbol{ToF}$: Time Need from Transmitter to receiver

Sound Speed

$\boldsymbol{V_s} = 343\ m/s$

Ultrasonic Distance (d)

$$\boldsymbol{d} = \frac{ToF\ * V_s}{2}$$

Introduction to Automotive Ultrasonic Sensing

Advantages of Ultrasonic Sensors in Vehicles

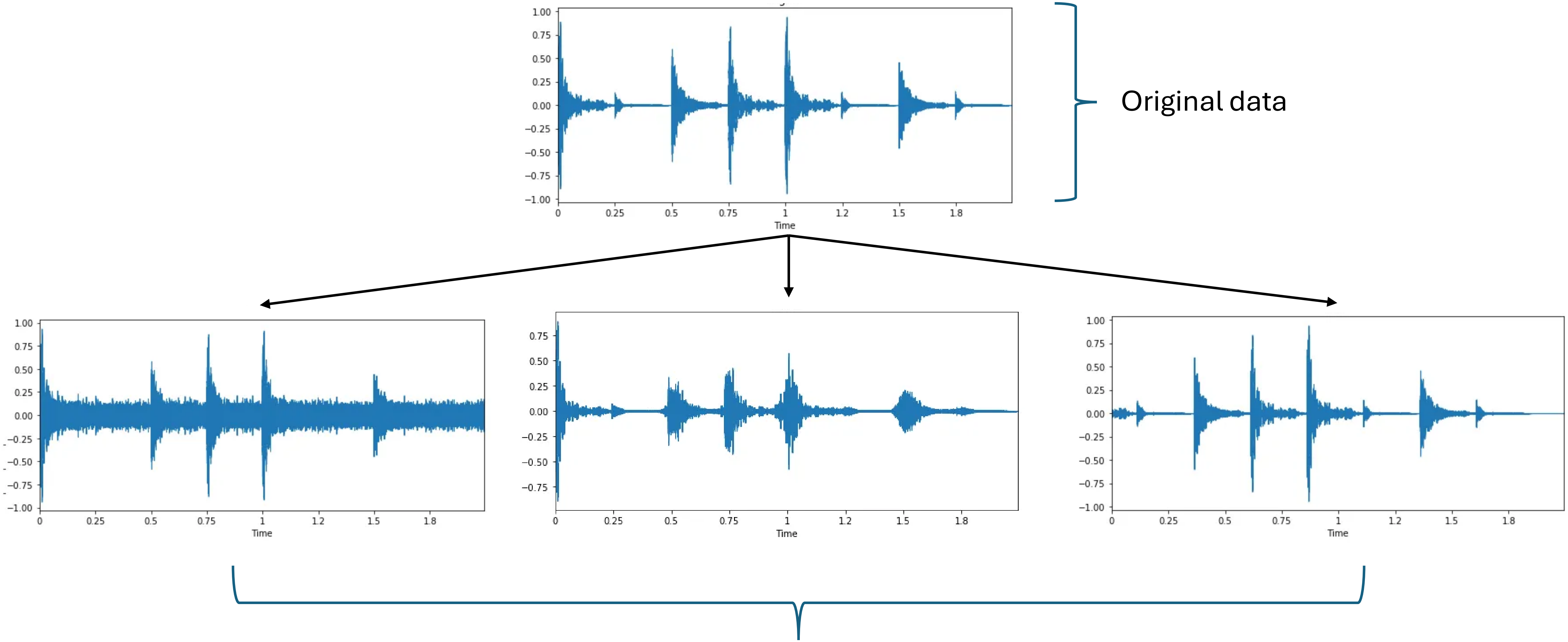
Parking Assistance Systems

Collision Avoidance Systems

Obstacle Detection

Blind Spot Monitoring

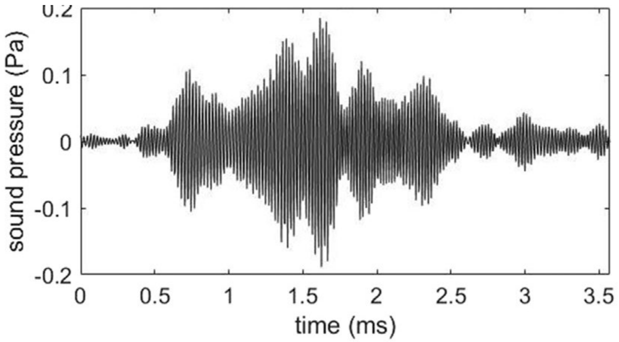
Data Augmentation



Data Augmentation

Offline augmentation methods:

dynamically modifies the data during the training process.
Applied to Raw-Data Representations



Advantages:

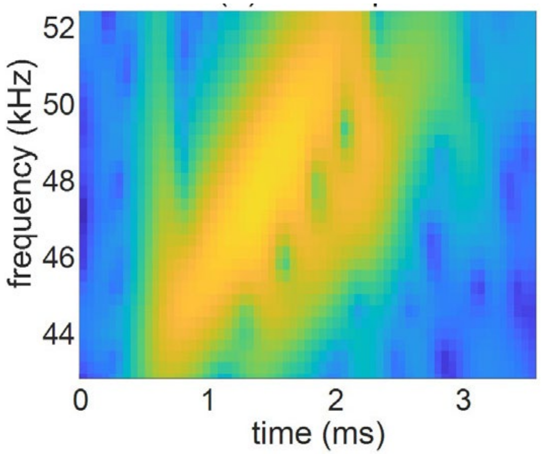
- ✓ Scalability in Pretraining
- ✓ Preprocessing Efficiency
- ✓ Reusability

Disadvantage:

- Slower (Done on CPU)
- More Storge required

Online augmentation methods:

precompute transformation before training
Applied to Time-Frequency Representations (Scalograms)



Advantages:

- ✓ No Disk Storage Required
- ✓ Faster (done on GPU)
- ✓ Model deployment is easier

Disadvantage:

- Increased Computational Overhead
- Risk of Overloading the Training Pipeline

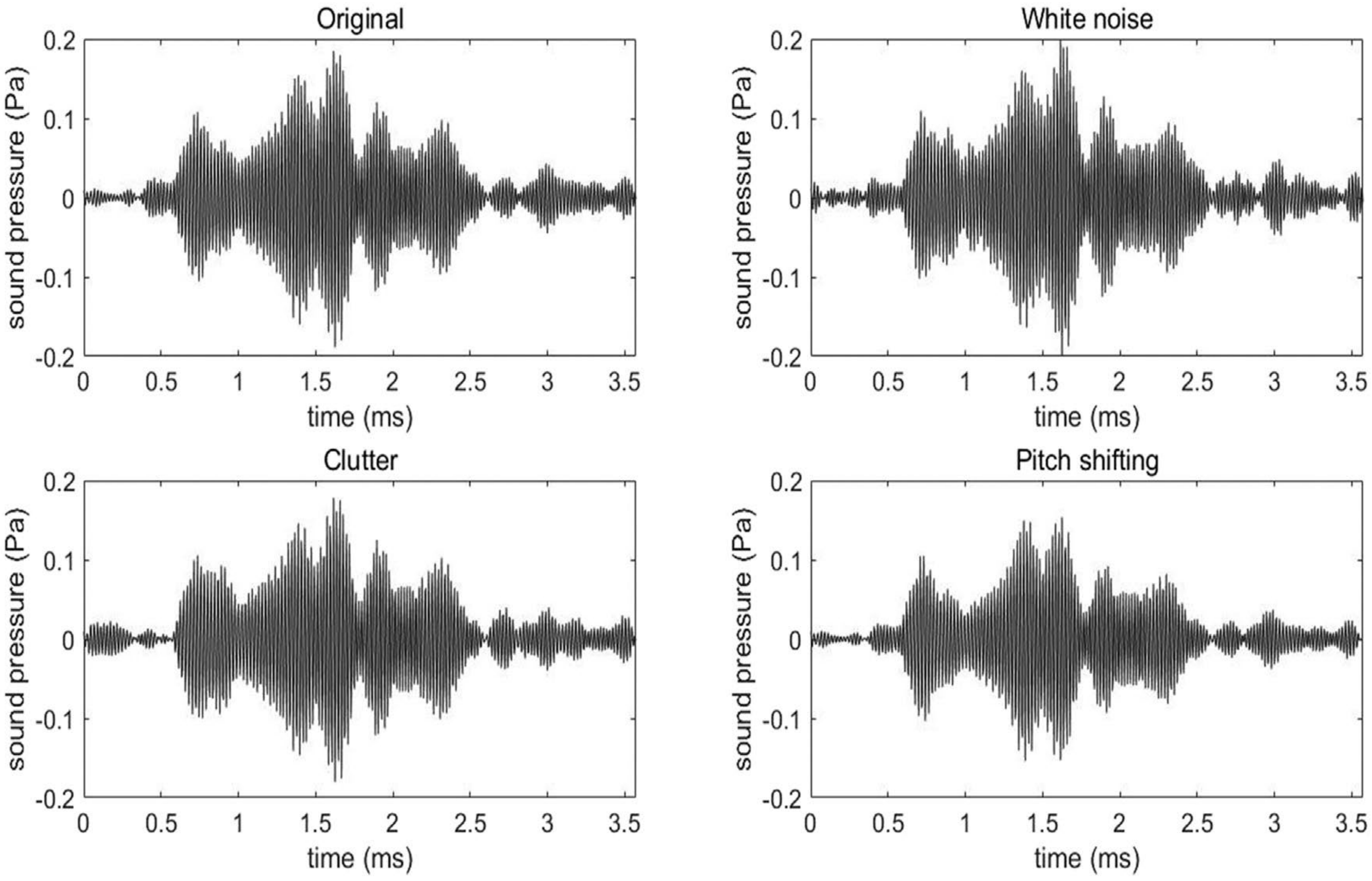
Data Augmentation

Offline augmentation methods:

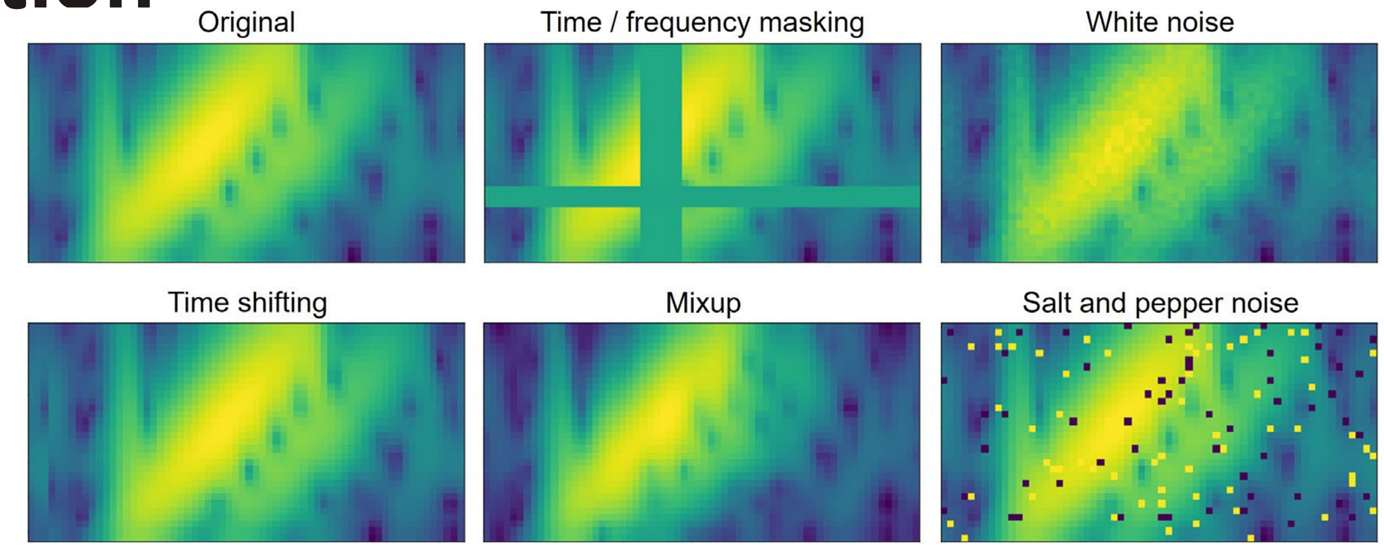
White noise: Injection of white Gaussian noise
Purpose: Improves robustness to real-world noise variations

Clutter: Superimposes irrelevant or unrelated signals to simulate environments with multiple objects or echoes.
Purpose: Enhances the model's ability to distinguish target objects from background noise.

Pitch shifting: Alters the frequency of the signal to mimic changes in material properties or Doppler effects.
Purpose: Improves the model's generalization across different operating conditions.



Data Augmentation



Online augmentation methods:

Frequency Masking: Randomly obscures certain frequency ranges in the scalogram or spectrogram.
Purpose: Forces the model to rely on other frequencies, improving robustness.

Time masking: Temporarily mutes specific time intervals in the time-frequency representation
Purpose: Simulates signal occlusions or missing data in real-world conditions.

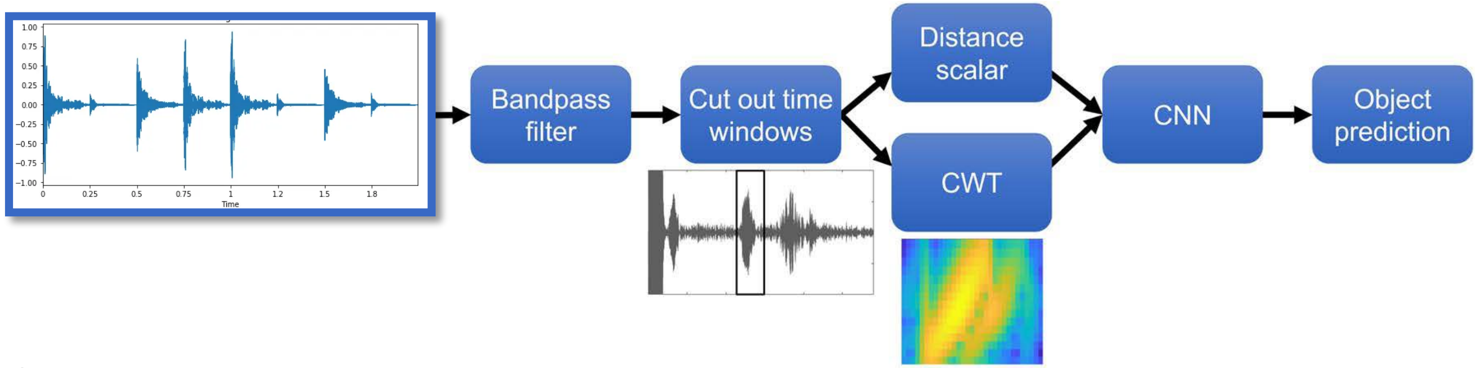
Salt and pepper noise: Adds random high-intensity noise (black or white pixels) to scalogram images
Purpose: Mimics sensor errors or extreme interference

White noise: Dynamically adds Gaussian noise to the data during training.
Purpose: Continuously simulates environmental variations

Time shifting: The scalogram image is shifted for s pixel steps either to the left or to the right.
Purpose: Improves the model's ability to handle temporal misalignments.

Multi-class and single-class mixup: Combines two signals (from the same or different classes) by mixing their time-domain or frequency-domain representations.
Purpose: Enhances the model's robustness to overlapping signals and improves generalization.

Signal Processing and Feature Extraction

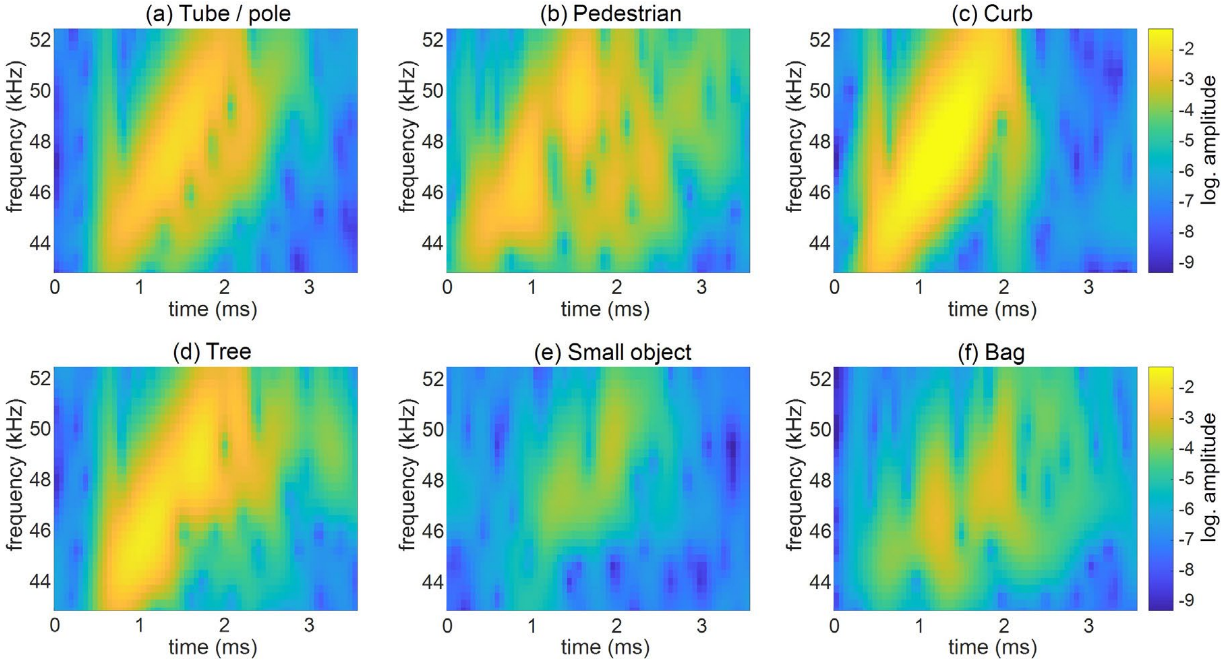


Bandpass Filtering:
Removes unwanted noise, such as environmental sounds.

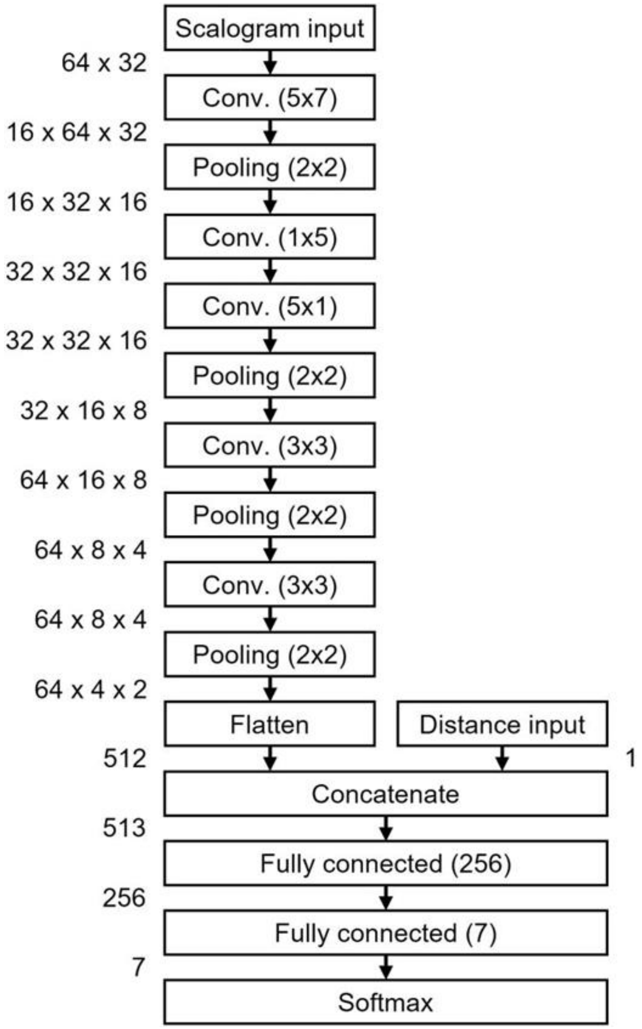
Continuous Wavelet Transform (CWT):
Converts time signals into scalograms (time-frequency images).

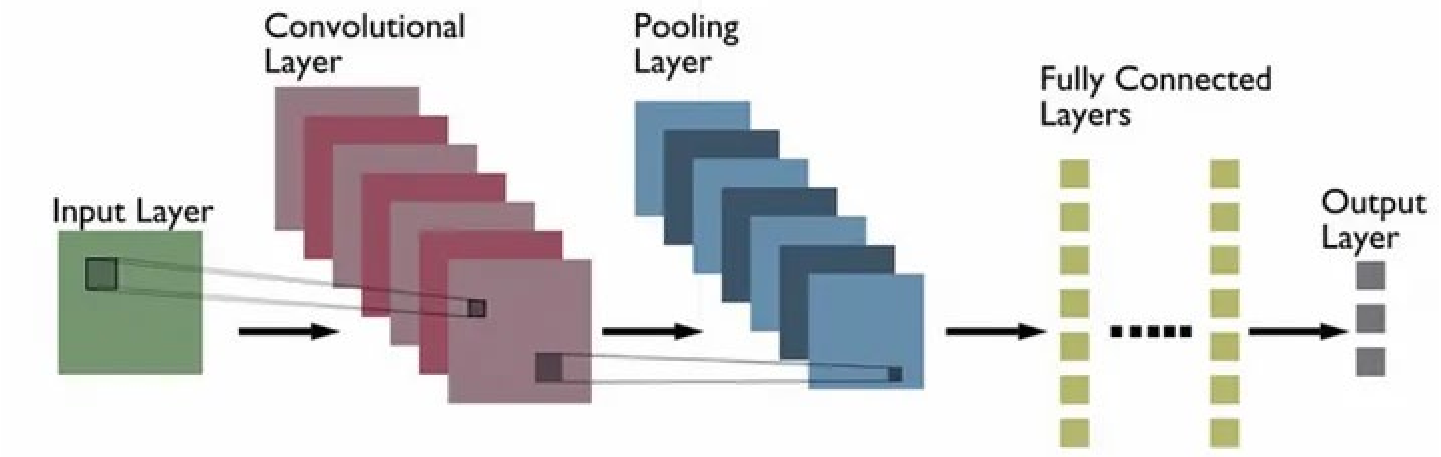
Signal Normalization:
Scales the amplitude of signals to a standard range, making them comparable across different conditions.

Scalogram Examples:
Visual examples of backscatter from different objects: Tube, Pedestrian, Curb, Tree, Small Object



CNN for Ultrasonic Sensing in Object Classification





Feature Extraction:
CNNs use convolutional layers to automatically extract key features such as edges, shapes, and textures from the input data.

Pooling Layers:
Pooling layers reduce the spatial dimensions of feature maps, lowering computational cost and helping prevent overfitting.

Classification:
Fully connected layers process the extracted features to classify the input data into predefined categories.

Experimental Results and Performance Evaluation

CNN#1: Baseline model, which might be a simpler or established CNN architecture.

CNN#2: The newer, improved or modified architecture that is being proposed for the specific task, in this case, ultrasonic object classification.

Table shows that **CNN#2** outperforms **CNN#1** in both the lab and field environments.

For object classes, CNN#2 achieves an accuracy of 86.7% (lab) and 65.4% (field).
In comparison, CNN#1 shows a drop in accuracy by 3.8% (lab) and 4.3% (field).

For Traversability classes, CNN#2 reaches 94.9% (lab) and 90.6% (field), whereas CNN#1 shows a drop of 2.7% (lab) and 3.2% (field).

	Mean accuracies ± standard deviation (%)			
	Lab environment		**Field environment**	
	Object class	**Traversability class**	**Object class**	**Traversability class**
CNN#1: no augmentation	82.9 ± 0.4	92.2 ± 0.4	61.1 ± 0.4	87.4 ± 0.4
CNN#2: no augmentation	86.7 ± 0.4	94.9 ± 0.3	65.4 ± 0.1	90.6 ± 0.3
Offline				
White noise	88.1 ± 0.3	95.9 ± 0.2	65.5 ± 0.1	91.4 ± 0.2
Clutter	86.8 ± 0.3	94.7 ± 0.2	64.9 ± 0.5	90.2 ± 0.2
Pitch shifting	85.5 ± 0.6	93.5 ± 0.3	63.3 ± 0.4	89.1 ± 0.3
Online				
Frequency masking	87.6 ± 0.3	95.3 ± 0.3	65.6 ± 0.2	91.0 ± 0.3
Time masking	87.7 ± 0.3	95.6 ± 0.1	65.8 ± 0.2	91.1 ± 0.2
Salt and pepper noise	87.6 ± 0.4	95.4 ± 0.3	65.2 ± 0.1	91.2 ± 0.2
White noise	86.7 ± 0.2	94.6 ± 0.2	65.2 ± 0.5	90.8 ± 0.2
Time shifting	88.6 ± 0.5	95.5 ± 0.2	**66.4** ± 0.2	91.3 ± 0.2
Single-class mixup	87.4 ± 0.5	95.3 ± 0.4	65.3 ± 0.1	90.8 ± 0.2
Multi-class mixup	87.1 ± 0.5	95.2 ± 0.2	65.4 ± 0.3	90.7 ± 0.3
Combinationa	**90.1** ± 0.3	**96.4** ± 0.1	66.2 ± 0.2	**91.5** ± 0.2

Conclusion

Single Sensor Classification:
Low-cost ultrasonic sensor classifies obstacles with high accuracy, considering Traversability and object types.

CNN Architecture: Proposed CNN using time-frequency images and distance data outperforms baseline CNN (LeNet-5-like).

Challenges with Small Object Discrimination: it is difficult due to clutter reflections.

Impact of Data Augmentation: Methods like white noise, frequency masking, and time shifting improve accuracy, but careful selection is key.

Best Results with Augmentation: Achieved 90.1% (lab) and 66.2% (field) accuracy for object classes, and 96.4% (lab) and 91.5% (field) for Traversability.

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