Geometrical Reconstruction using Acoustic Tactile Sensing

Can a Robot Hear Whether It Touches Something?

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Motivation

The Core Idea

Every sensor creates representations

- Cameras $\rightarrow$ Images of the environment
- LiDAR $\rightarrow$ 3D point clouds
- Force sensors $\rightarrow$ Contact force maps

Why not acoustic sensors?

If a robot finger has a microphone, it should also create a representation of what it touches!

The Vision

Reconstruct what the finger touches

Not replacing cameras — but sensing what cameras **cannot** see

Why Start With Geometry?

- Geometric shapes are **building blocks**
- Screws, buttons, edges, holes...
- Complex objects = combinations of primitives
- **If we can reconstruct geometry,** we can reconstruct anything

Project Goal

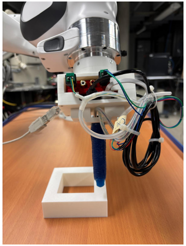
Can acoustic sensing create visual representations of touched surfaces?

Binary contact classification $\rightarrow$ Surface reconstruction

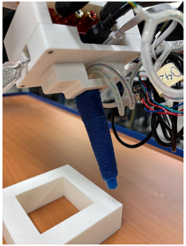
Setup

Full Setup

Sensor Mounting



Close-up



Why Use a Robot? — It's Part of the System!

- ✔ **Mechanically coupled:** Sound travels through arm joints and links to the microphone
- ✔ **Real-world relevance:** In actual deployment, the sensor *will* be on a robot
- ✔ **Controlled experiments:** Systematic, repeatable data collection across configurations

The Hidden Challenge: Robot Arm Affects the Signal

⚠ The Problem

The robot arm is part of the acoustic system

Sound waves travel through:

Surface → Probe → **Robot Arm** → Microphone

What This Means

- **Different arm positions** = Different acoustic responses
- Joint angles change wave propagation paths
- Same contact event sounds **different** at different positions

The Key Insight

Signal = Contact Information ⊗ Arm Configuration

The signal contains **both** — they are entangled!

(Also observed in VibeCheck [Zoller et al., 2024])

Why Multiple Workspaces?

WS1: Position A

Arm config θ_1

WS2: Position B

Arm config θ_2

WS3: Position C

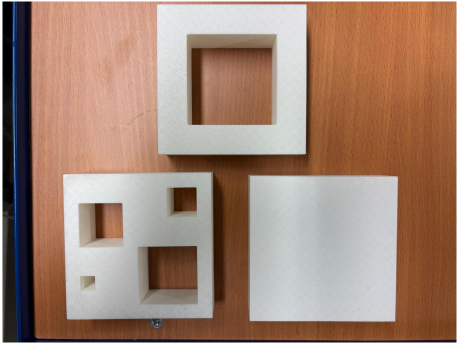
Arm config θ_3

Question:

Will a classifier trained at one position work at another?

Data Collection: Objects and Workspaces

Test Objects



A: Cutouts — B: Empty — C: Full — D: Big Cutout

Complete Dataset Overview

	Obj A Cutouts	Obj B Empty	Obj C Full	Obj D Big Cut
WS1	✓	✓	✓	
WS2	✓	✓	✓	
WS3	✓	✓	✓	
WS4				✓

Green: Proof of Concept data (A,B,C in WS1-3)

Red: Final Validation data (D in WS4)

?

Can we reconstruct geometric shapes using binary surface classification?

Task

Binary classification

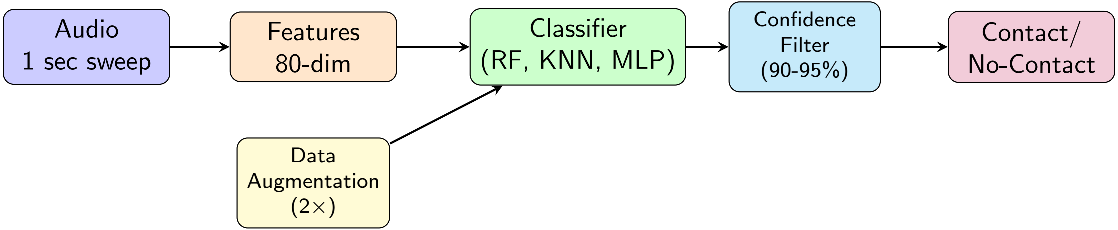
Contact vs. No-Contact

Target

Geometric reconstruction

on data from the same distribution

Method: Acoustic Feature Classification



80-Dimensional Features

- **MFCCs + Deltas** (39): Frequency content
- **Spectral** (11): Energy distribution
- **Temporal** (15): Contact dynamics
- **Impulse Response** (15): Resonance

Data Augmentation

- Noise injection
- Time shifting
- Pitch variation
- Gain scaling
- Time stretching

Why Hand-Crafted?

- Hand-crafted: **70%**
- Spectrograms: **59%**
- 80 vs 10,240 dims

Result: Excellent Classification on Data From Same Distribution

~99%

Test Accuracy

(Known surfaces & configurations)

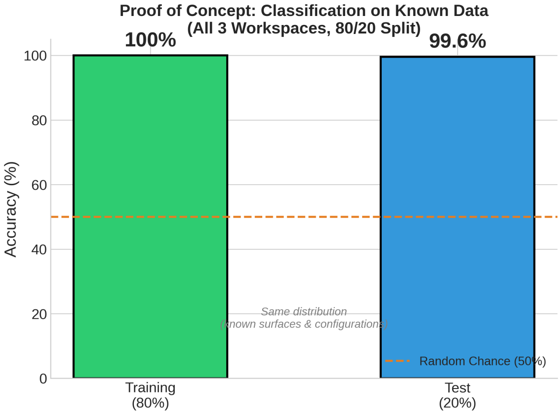
Dataset Split

3 Objects × 3 Workspaces

Training: 80%

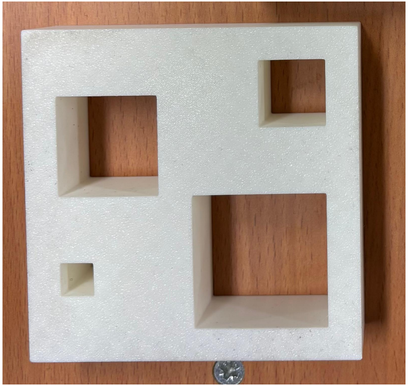
Test: 20%

Same distribution

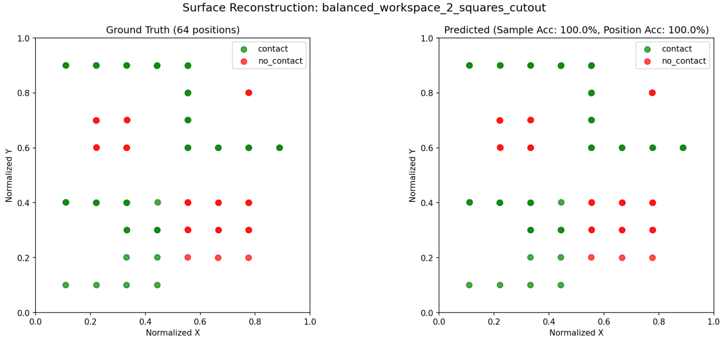


Reconstruction: Excellent Performance on Test Data

Object View

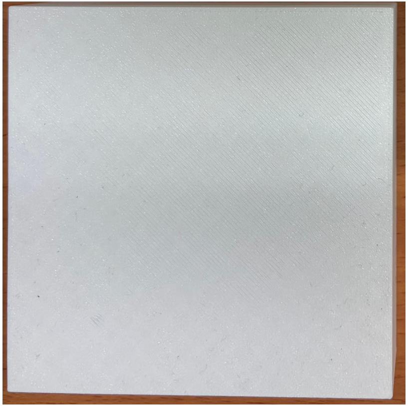


Ground Truth vs Prediction

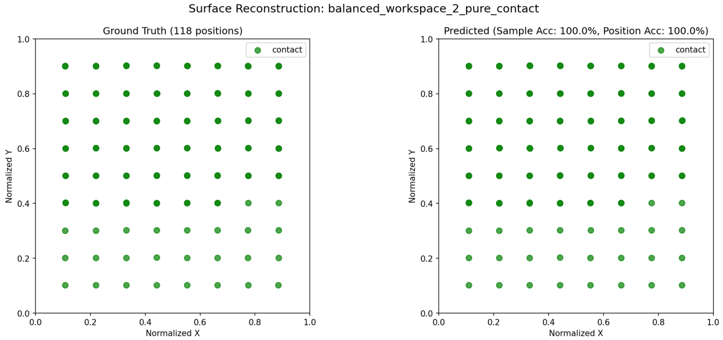


Reconstruction: Full Contact Surface

Object View

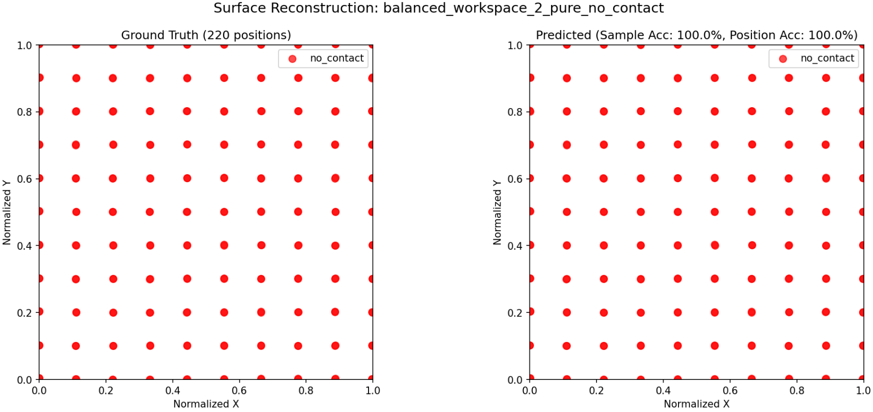


Ground Truth vs Prediction



Reconstruction: No-Contact Surface

Ground Truth vs Prediction



Now: Testing Generalization

Proof of Concept Achieved!

Acoustic contact classification works on data from the same distribution

$\sim$100% test accuracy with excellent reconstruction

But does it generalize?

Two critical questions:

What if we test on a **new workspace**?

Train: WS1+WS3 $\rightarrow$ Test: WS2

Same objects, **different robot positions**

→ Configuration Generalization

What if we test on a **new object**?

Train: A,B,C $\rightarrow$ Test: D (+ new workspace)

Completely unseen object & workspace

→ Object Generalization

Challenge 1: Configuration Generalization

Experimental Setup

Training: WS1 + WS3

WS1 WS3

Same objects (A, B, C)

↓

Validation: WS2 (unseen)

WS2

Same objects, different robot configurations

Performance Results

Dataset	**Accuracy**
Training (WS1+WS3)	**100%**
Test (WS1+WS3, 20%)	$\sim$**100%**
Validation (WS2)	**65-70%**

Configuration Entanglement

65-70%

Better than random (50%), but significant drop

Signal = Contact $\otimes$ Configuration

Model partially learned configuration-specific features.

More diverse workspace data likely needed.

Challenge 2: Object Generalization

Object Generalization Setup

Training: 3 Objects (A, B, C)

A: Cutouts | B: Empty | C: Full

Train: WS1 + WS2 + WS3

↓

Hold-out: Object D

D: Big Cutout

Test: WS4 (new)

New object + new workspace

Complete generalization test

Performance Results

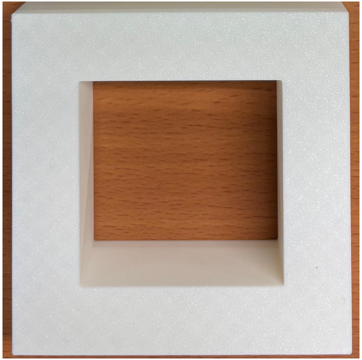
Dataset	Accuracy
Training (A,B,C on WS1-3)	100%
Test (A,B,C on WS1-3)	∼100%
Hold-out (D on WS4)	**50%**

Critical Discovery

50% = Random Chance

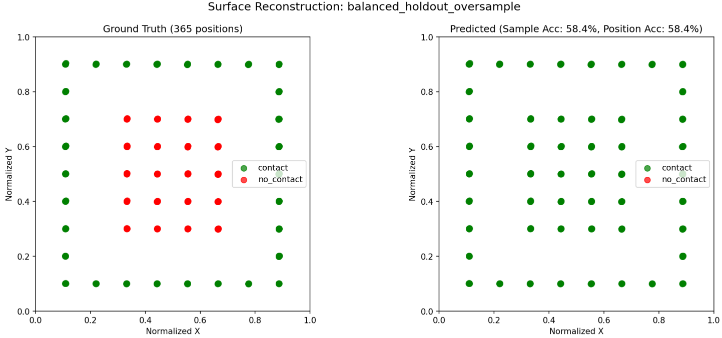
Model completely fails on unseen object

Reconstruction on New Object + Workspace Fails



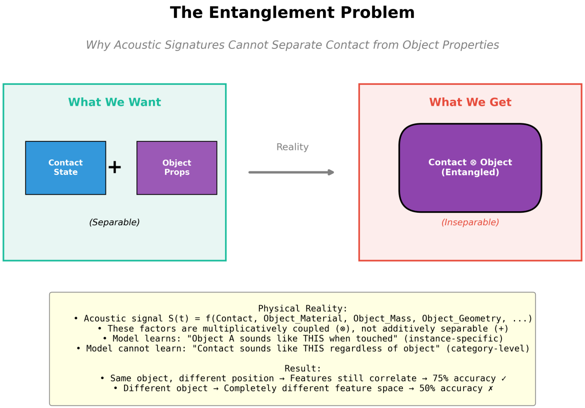
New Object + WS

Train: A-C → Test: D on WS4



50%

Understanding the Failure: The Entanglement Problem



The Core Problem

$$\textbf{Signal} = \textbf{Contact} \otimes \textbf{Object}$$

The acoustic signature contains **BOTH**:

1. Contact state information
2. Object identity information

Physics Explanation

- Each object has unique eigenfrequencies
- Material, size, geometry, mass affect acoustic response
- Model learned **“Object A contact”** not **“contact in general”**

Conclusions

Main Achievement: Proof of Concept

"Acoustic-based geometric reconstruction IS POSSIBLE"

(on data from the same distribution: $\sim$100% test accuracy, excellent reconstruction)

What Works

- $\sim$**99%** test accuracy (known surfaces & configurations)
- Excellent surface reconstruction
- Hand-crafted features outperform spectrograms (70% vs 59%)
- 128$\times$ fewer features, better results

Discovered Limitations

- **Configuration entanglement:** 65-70% on unseen workspace
  Signal $=$ Contact $\otimes$ Configuration
- **Object entanglement:** 50% on unseen object (random)
  Signal $=$ Contact $\otimes$ Object

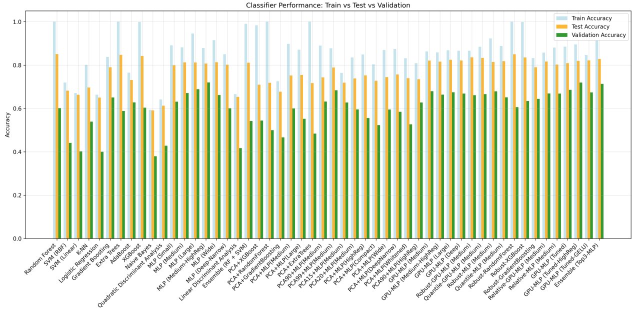
Future Directions

- **Configuration invariance:** Collect data from many more diverse workspaces/positions
- **Object invariance:** Train on many varied objects to disentangle contact from object identity

Thank You — Questions?

Questions?

Backup: All Classifiers Comparison



Top Classifiers (Validation)

Classifier	Val Acc.
MLP (Medium-HighReg)	**72.0%**
GPU-MLP (Tuned-HighReg)	71.9%
Ensemble (Top3-MLP)	71.3%
MLP (Large)	68.9%
GPU-MLP (Tuned)	68.6%
Gradient Boosting	65.1%
Random Forest	60.1%

Key Finding

MLPs with regularization outperform tree-based methods on validation data

Backup: 80-Dimensional Feature Set

MFCCs + Deltas (39 dims)

- 13 MFCC coefficients
- 13 MFCC delta (velocity)
- 13 MFCC delta-delta (acceleration)

Spectral Features (11 dims)

- Spectral centroid
- Spectral bandwidth
- Spectral rolloff
- Spectral flatness
- Spectral contrast (7 bands)

Temporal Features (15 dims)

- Zero-crossing rate
- RMS energy
- Mean, std, skewness, kurtosis
- Onset strength
- Tempo estimation

Impulse Response (15 dims)

- Transfer function peaks
- Decay characteristics
- Resonance frequencies
- Damping coefficients

Backup: Object and Workspace Details

Training Objects (A, B, C)

- **Object A:** Cutouts
  Wooden board with geometric cutouts
- **Object B:** Empty
  Plain wooden surface
- **Object C:** Full
  Wooden board with filled shapes

Hold-out Object (D)

- **Object D:** Big cutout
  Larger wooden board with single large cutout
- Tested in WS4 only
- Never seen during training

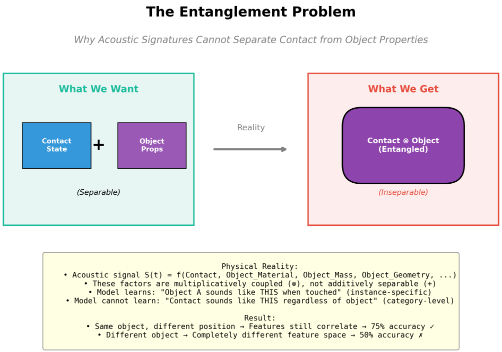
Configuration Generalization Test

- **Train:** WS1, WS3 (Objects A,B,C)
- **Validate:** WS2 (Objects A,B,C)
- Tests **configuration generalization**
- Result: **65-70%** (partial)

Object Generalization Test

- **Train:** WS1,2,3 (Objects A,B,C)
- **Hold-out:** WS4 (Object D)
- Tests **object generalization**
- Result: **50%** (random)

Backup: The Entanglement Problem Explained



Two Entanglement Problems

1. **Signal = Contact $\otimes$ Configuration**
   Robot pose affects acoustic response
2. **Signal = Contact $\otimes$ Object**
   Object identity entangled with contact

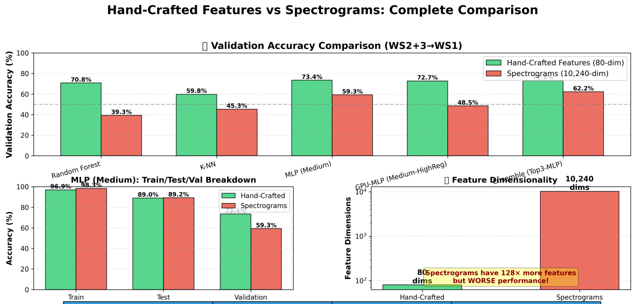
Physics Explanation

- Robot pose affects wave propagation
- Each object has unique eigenfrequencies
- Material, size, geometry affect response

Implications

- Not failures — **discoveries**

Backup: Hand-Crafted Features vs Spectrograms



Metric	Hand-Crafted (80-dim)	Spectrograms (10,240-dim)	Winner
Feature Dimensions	80	10,240	Hand-Crafted (128× smaller)
Best Validation Acc	73.4%	62.2%	Hand-Crafted
MLP Validation Acc	73.4%	59.3%	Hand-Crafted
RF Validation Acc	70.8%	39.3%	Hand-Crafted
Training Samples	10,639	3,546	Hand-Crafted (3× more data)
Overfitting Risk	Lower (smaller model)	Higher (128× more params)	Hand-Crafted

CONCLUSION: Hand-Crafted Features are BETTER for Our Use Case

- **73.4% vs 62.2% validation accuracy (11.3% improvement)**
- **128× fewer features (80 vs 10,240) → faster, less overfitting**
- **More interpretable (MFCCs, spectral, temporal, impulse response)**
- **Better generalization despite smaller model size**

Key Results

Validation Accuracy (WS2+3→WS1):

- **Hand-Crafted: 73.4%**
- Spectrograms: 59.3%
- **+14.1% improvement!**

Why Hand-Crafted Wins

- **128× fewer features** (80 vs 10,240)
- **Less overfitting** with limited data
- **More interpretable** features
- **Faster inference** (¡1ms)
- **Better generalization**