

Acoustic Sensing for Robotic Touch

Can Robots "Hear" What They're Touching?

Georg Wolnik

TU Berlin Robotics Lab

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Can acoustic signals enable robots to understand what they're touching?

What we did:

- Recorded 1,931 audio samples from different touch scenarios
- Ran 6 experiments to test acoustic sensing capabilities
- Found clear answers about what works and what doesn't

Bottom line: **YES** - but it depends on the task!

Our Test Datasets

Table: What We Tested

Dataset	Scenario	Classes	Samples
Batch 1	Position detection (4 spots)	4	387
Batch 2	Position validation test	4	352
Batch 3	Edge vs No-edge (binary)	2	298
Batch 4	Material detection (wood/metal)	2	264
Edge v1	Complex edge detection	3	630
Total	Multiple scenarios	2-4	1,931

Each dataset tested with 6 different experiments to understand acoustic sensing from every angle.

Our 6 Experiments

① Data Quality Check

Is our audio data good enough?

② Visualization & Separation

Can we see differences between classes?

③ AI Classification

Which algorithms work best?

④ Feature Importance

Which audio features matter most?

⑤ Neural Network Analysis

What do deep learning models focus on?

⑥ Physics Understanding

What's the science behind acoustic sensing?

Experiment 1: Data Quality Check

Question: Is our recorded audio data good enough for analysis?

How we tested:

- Counted samples per class (balance check)
- Measured signal-to-noise ratio
- Extracted 38 acoustic features
- Checked for corruption/missing data

Batch	Samples	Balance	Quality
Position (1&2)	387, 352	98-99%	Excellent
Edge Binary	298	98%	Excellent
Material	264	100%	Excellent
Edge 3-class	630	100%	Excellent

Result: **All data is high quality!** SNR \geq 40dB, perfect feature extraction.

Experiment 2: Visualization & Class Separation

Question: Can we visualize differences between touch types?

How we tested:

- PCA: Find most important data directions
- t-SNE: Create 2D maps of similarity
- Silhouette scores: Measure class separation

Task	Silhouette Score	Separability
Material Detection	0.463	Excellent
Edge Binary	0.347	Good
Position Detection	0.184-0.191	Moderate
Edge 3-class	-0.015	Poor

Key Insight: Task complexity = visualization difficulty. Material detection shows clear acoustic signatures!

Experiment 3: AI Classification - The Big Test

Question: Can AI algorithms learn to classify touch types from acoustic features?

How we tested:

- 7 algorithms: Random Forest, SVM, Gradient Boosting, Neural Networks...
- 5-fold cross-validation for reliability
- Compared performance across all scenarios

Task	Best Accuracy	Status
Material Detection	95%	Ready for robots!
Edge Binary	90%	Ready for robots!
Position Detection	78%	Needs engineering
Edge 3-class	67%	Challenging

Clear winner: Material detection. Different materials = completely different acoustic signatures!

Why Some Tasks Work Better Than Others

Material Detection (95% - Excellent):

- Wood vs metal = completely different acoustic resonances
- Even simple algorithms work perfectly
- Clear frequency signatures

Edge Binary (90% - Excellent):

- Edge contact creates sharp acoustic transients
- Clear temporal (timing) differences
- SVM algorithm works best

Position Detection (78% - Moderate):

- Spatial differences are subtle but detectable
- Needs ensemble methods (Random Forest)
- Consistent across validation tests

Edge 3-class (67% - Hard):

- Contact/Edge/No-contact states overlap acoustically
- Only Gradient Boosting reaches 67%
- Fundamental acoustic similarity between classes

Experiment 4: Which Audio Features Matter Most?

Question: Which acoustic features are most important for each task?

How we tested:

- Remove features one by one
- Measure performance drop when missing
- Rank by importance

Task	Spectral	Temporal	Statistical	Perceptual
Material	67%	8%	12%	18%
Edge Binary	42%	58%	15%	12%
Position	34%	19%	12%	16%
Edge 3-class	28%	22%	20%	19%

Key Insights:

- **Material:** Frequency content dominates (spectral)
- **Edge:** Timing changes matter most (temporal)
- **Position:** Needs balanced feature combination

Experiment 5: What Do Neural Networks See?

Question: What do neural networks pay attention to when making decisions?

How we tested:

- Trained neural networks on each dataset
- Used gradient-based saliency analysis
- Compared with feature ablation results

Task	Neural Net	Best Traditional	Insight
Material	92%	95% (RF)	Any method works
Edge Binary	87%	90% (SVM)	Traditional sufficient
Position	72%	78% (RF)	Trees handle complexity b
Edge 3-class	54%	67% (GB)	Ensembles essential

Key Finding: For simple tasks, traditional ML is better. For complex tasks, neural networks reveal alternative feature combinations.

Experiment 6: The Physics Behind Acoustic Sensing

Question: What's physically happening when robots "hear" touch?

How we tested:

- Extracted acoustic "impulse responses"
- Measured resonant frequencies and damping
- Analyzed physical acoustic properties

Example: Edge Detection Physics

Contact State	Duration	Frequency	Physics
Contact	56 ms	2.0 kHz	Stable coupling
Edge	42 ms	2.8 kHz	Sharp interface
No Contact	23 ms	1.2 kHz	Diffuse scattering

Result: Physics-only features achieved 52% accuracy on the hardest task.

The science is real!

Summary: Can Acoustic Sensing Work for Robotics?

YES - but it depends on what you want to detect

Task Difficulty Ranking:

- 1 **Material Detection (95%):** READY FOR ROBOTS NOW
- 2 **Binary Edge Detection (90%):** READY FOR DEPLOYMENT
- 3 **Position Detection (78%):** NEEDS ENGINEERING
- 4 **3-Class Edge Detection (67%):** RESEARCH NEEDED

What makes it work:

- Different materials = different acoustic resonances
- Contact geometry affects acoustic coupling
- Edge interfaces create sharp acoustic transients
- The physics is measurable and predictable

Practical Implementation Guidelines

For Robot Developers:

Ready for Deployment:

- **Material discrimination systems** - Use spectral features, any algorithm works
- **Binary edge detection** - Focus on temporal dynamics, use SVM

Feasible with Engineering:

- **Position detection** - Use ensemble methods, expect 78% accuracy
- **Simple spatial discrimination** - Requires balanced feature sets

Research Needed:

- **Complex multi-class problems** - Need advanced ensemble methods
- **Noise robustness** - Real-world environment testing
- **Real-time optimization** - Processing speed improvements

Technical Implementation Recommendations

Table: Algorithm & Feature Recommendations

Task	Best Algorithm	Key Features
Material Detection	Random Forest	Spectral contrast, frequency content
Edge Binary	SVM (RBF)	Zero-crossing rate, temporal dynamics
Position Detection	Random Forest	Spectral centroid, bandwidth
Complex Tasks	Gradient Boosting	All 38 features combined

Processing Requirements:

- **Material detection:** ≤ 10 ms latency possible
- **Edge detection:** ≤ 15 ms latency achievable
- **Complex tasks:** ≤ 35 ms with optimization

Implementation tip: Start with material detection - it's the most reliable and easiest to implement!

Future Research Directions

Immediate Opportunities:

- **Multi-modal fusion:** Combine acoustic + visual + tactile
- **Real-world validation:** Test in noisy environments
- **Online learning:** Adaptive systems that improve with use

Advanced Research:

- **Dynamic contact analysis:** Track contact changes over time
- **Physics-informed features:** Better use of acoustic science
- **Cross-platform generalization:** Work across different robots

Applications Ready Today:

- Quality control (material verification)
- Grasping assistance (edge detection)
- Safety systems (contact monitoring)

Acoustic sensing is a practical and reliable technology for robotic touch discrimination

Key Achievements:

- **95% accuracy** for material detection - better than many vision systems
- **90% accuracy** for binary edge detection - useful for manipulation
- **Clear understanding** of what works, what doesn't, and why
- **Practical implementation guidelines** for real-world deployment

The technology is ready for specific applications today, with clear paths for expanding capabilities.

Questions?