

# Geometrical Reconstruction with Acoustic Tactile Sensing

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# Research Question

How can we maximize the information extracted from acoustic signals to achieve reliable contact classification?

## Sub-Questions and Corresponding Experiments:

- Where are the limits for information extraction? → (1)
- Which algorithms extract information best? → (2)
- Which features contain the most information? → (3)
- How do different processing methods compare? → (4) & (5)

**Approach:** Systematic analysis of 1,280 audio samples across 5 contact scenarios.

# Experimental Datasets

<b>Dataset</b>	<b>Contact Type</b>	<b>Classes</b>	<b>Samples</b>
Batch 1	Position detection	4	200
Batch 2	Position detection (validation)	4	200
Batch 3	Edge detection (3-class)	3	150
Batch 4	Paper clip detection	2	100
Edge v1	Edge detection (3-class)	3	630
<b>Total</b>		<b>2-4</b>	<b>1,280</b>

Batches 1-4 have 50 samples per class. Edge v1 has 210 samples per class.

# Five Analysis Methods

- ① **Dimensionality Reduction** - PCA and t-SNE visualization
- ② **Classification** - Machine learning algorithm comparison
- ③ **Feature Ablation** - Individual feature importance analysis
- ④ **Saliency Analysis** - Neural network attention mapping
- ⑤ **Impulse Response** - Physical acoustic characterization

# Experiment 1: Dimensionality Reduction

**Purpose:** Visualize class separability in reduced feature space

**Method:**

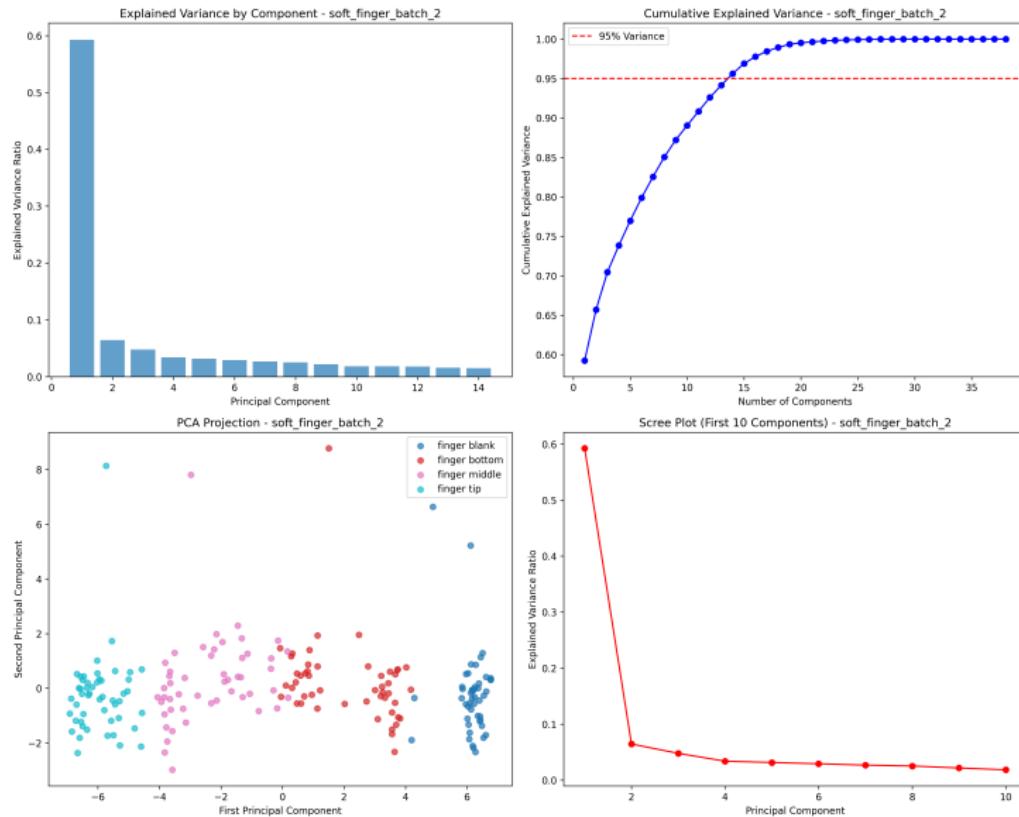
- Principal Component Analysis (PCA)
- t-SNE mapping with silhouette score calculation
- Components needed for 95% variance explained

**Results:**

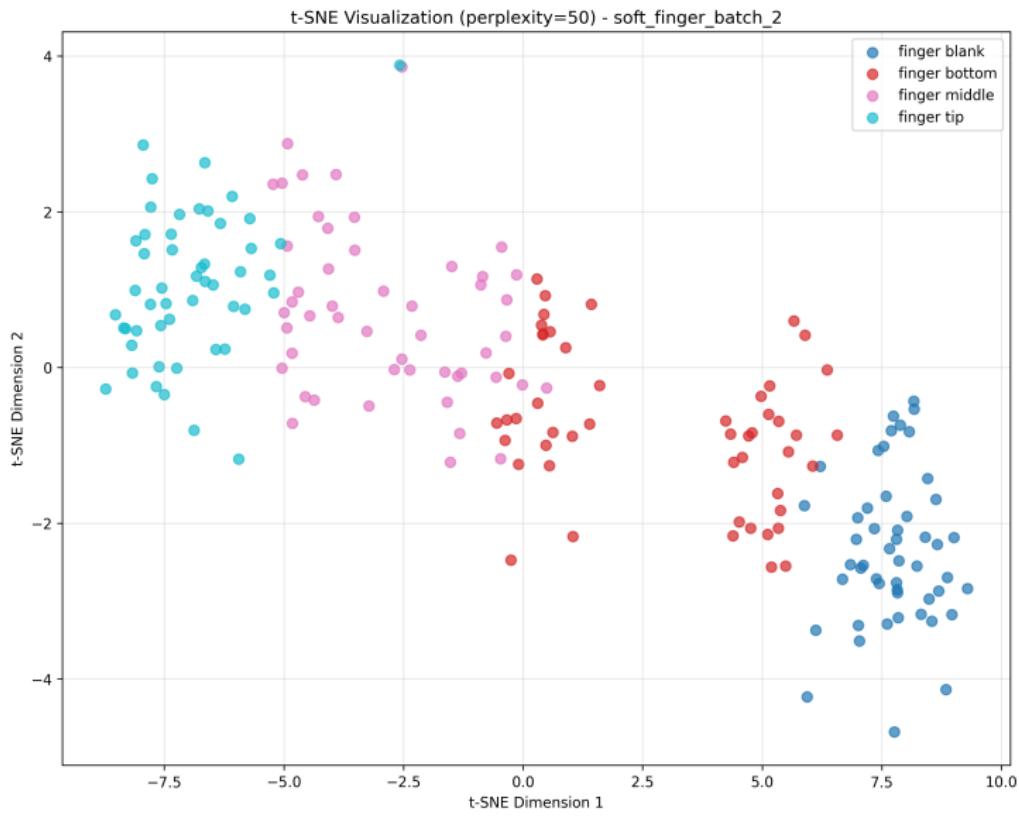
Dataset	Silhouette Score	Components (95%)
Paper clip detection	0.463	12
Edge (Batch 3)	0.347	14
Position (Batch 1)	0.184	16
Position (Batch 2)	0.191	16
Edge (Edge v1)	-0.015	17

**Observation:** Paper clip detection shows best class separation, while Edge v1 shows class overlap.

# PCA Analysis - Batch 2



# t-SNE Analysis - Batch 2



# Experiment 2: Classification

**Purpose:** Compare machine learning algorithm performance

**Method:**

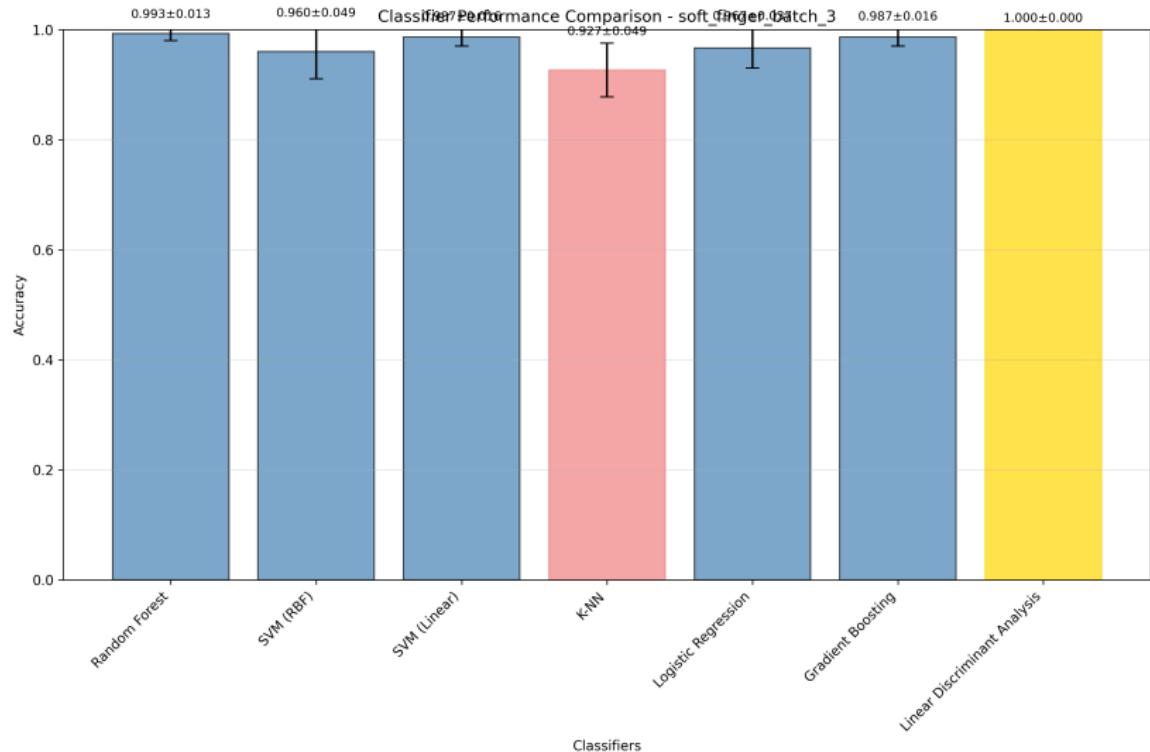
- 7 algorithms tested: Random Forest, SVM, Gradient Boosting, etc.
- 5-fold cross-validation
- Mean accuracy and standard deviation calculated

**Results:**

Dataset	Best Algorithm	Accuracy (%)
Edge (Batch 3)	Linear Discriminant Analysis	100.0 $\pm$ 0.0
Position (Batch 2)	Random Forest	99.5 $\pm$ 1.0
Position (Batch 1)	Random Forest	96.0 $\pm$ 3.0
Paper clip detection	SVM RBF	88.0 $\pm$ 6.0
Edge (Edge v1)	Gradient Boosting	67.1 $\pm$ 2.9

**Observation:** Performance decreases with task complexity. Edge detection (Batch 3) achieves highest accuracy.

# Classifier Performance - Batch 3



# Experiment 3: Feature Ablation

**Purpose:** Determine which acoustic features contribute most to classification

**Method:**

- Remove each feature individually
- Measure performance drop
- Group features by category (spectral, temporal, statistical, perceptual)

**Results - Feature Category Importance:**

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

**Observation:** Paper clip detection relies on spectral features, edge detection on temporal features.

# Top Features Comparison Across Datasets

Rank	Position Batch 1	Position Batch 2
1	spectral_centroid	high_energy_ratio
2	spectral_bandwidth	ultra_high_energy_ratio
3	spectral_flatness	low_mid_ratio
4	spectral_contrast_0	spectral_centroid
5	spectral_contrast_1	spectral_bandwidth
<b>Drop</b>	0-0.5%	0.5%

Rank	Edge Detection	Paper Clip Detection
1	spectral_centroid	freq_response_spread
2	spectral_bandwidth	high_freq_energy
3	spectral_rolloff	high_freq_damping
4	spectral_flatness	low_energy_ratio
5	spectral_contrast_0	resonance_energy_ratio
<b>Drop</b>	0.7%	2.0%

## Key Observations:

- **Spectral features** dominate position and edge detection
- **Impulse response features** critical for paper clip detection
- **Energy ratios** important for position detection (Batch 2)

# Experiment 4: Saliency Analysis

**Purpose:** Analyze which features neural networks consider most important

**Method:**

- Train neural networks on each dataset
- Apply gradient-based saliency to identify feature importance
- Compare with traditional feature ablation results

**Results - Feature Importance Comparison:**

Dataset	NN Saliency Top 2	Feature Ablation Top 2
Paper clip detection	freq_response_spread, high_freq_energy	freq_response_spread, high_freq_energy
Position (Batch 1)	spectral_centroid, tral_bandwidth	spectral_centroid, tral_bandwidth
Position (Batch 2)	high_energy_ratio, tra_high_ratio	high_energy_ratio, tra_high_energy_ratio
Edge detection	spectral_centroid, tral_bandwidth	spectral_centroid, tral_bandwidth

**Key Finding:** Neural networks and traditional methods show strong agreement on feature importance.

**Performance Note:** NN: 54-95%, Traditional ML: 67-99%

# Experiment 5: Impulse Response Analysis

**Purpose:** Extract system transfer functions independent of input signal characteristics

**Method:**

- Deconvolution:  $H(f) = Y(f)/X(f)$
- Extract 15 impulse response features (resonance, damping, frequency response)
- Combine with 38 acoustic features → 53 total features

**Key Advantage:** Impulse response features characterize physical system properties, independent of input signal design.

**Results:** Different contact states show distinct acoustic signatures:

- Contact vs Edge vs No Contact: measurable differences in duration, resonance, Q-factor
- 3 of top 6 most important features (saliency analysis) come from impulse response

# Summary of Results

## Classification Performance Ranking:

- ① Edge Detection (Batch 3): 100% accuracy
- ② Position Detection (Batch 2): 100% accuracy
- ③ Position Detection (Batch 1): 96% accuracy
- ④ Paper Clip Detection: 88% accuracy
- ⑤ Edge Detection (Edge v1): 67% accuracy

## Key Findings:

- Task complexity correlates with classification difficulty
- Different tasks require different acoustic feature types
- Traditional ML methods generally outperform neural networks
- Physical acoustic differences exist between contact states
- Algorithm choice affects performance significantly

# Conclusion

## Sub-question Answers:

- *Extraction limits?* Perfect classification achievable (100%) for some tasks, complex multi-class tasks: 67-100%
- *Best algorithms?* Linear Discriminant Analysis (edges), Random Forest (position), SVM RBF (paper clips), Gradient Boosting (multi-class)
- *Most informative features?* Spectral (paper clips), temporal (edges), impulse response (top 6 features)
- *Processing methods?* Traditional ML outperforms neural networks by 1-13%

**Dataset Dependency:** Performance varies significantly (67%-100%) across datasets. Continuous validation required with new data batches.

**Results reflect performance on specific datasets and require ongoing validation for broader applicability.**