Machine Learning Approaches for Biosonar Systems: Investigating Dynamic Sensing in Complex Natural Environments

Final Defense

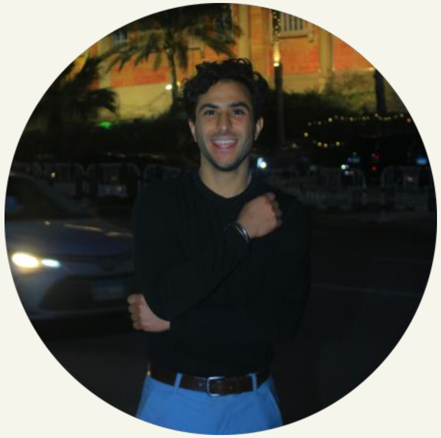
Ibrahim Eshera

Advisor:
Rolf Müller

Committee:
Alexander Leonessa
Jeff Reed
Creed Jones
Jin Ping Han

VIRGINIA TECH™

About Me



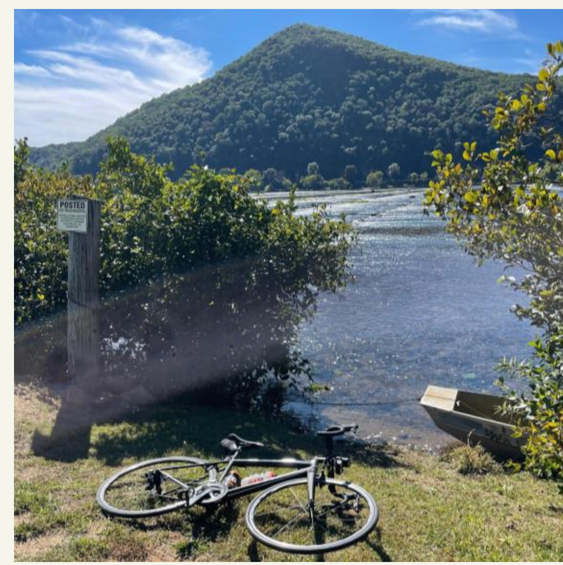
Ibrahim Eshera

Bachelors of Science
University of Maryland
Electrical Engineering

Master of Science
Virginia Tech
Electrical Engineering

PhD Candidate in Electrical Engineering
Acoustics, Machine Learning, Audio AI

Have worked at places like
Bosch Research,
Ford Autonomous Vehicles,
ARL United States Army Research Lab.



imeshera.github.io/home

Presentations & Publications

1. **Eshera, I.**, Duggal, G., & Müller, R. (2025). Deep Learning Methods for Assessing Time-Variant Nonlinear Signatures in Clutter Echoes. *Advanced Intelligent Systems*. **(Under Review)**

2. **Eshera, I.**, Lagad, S., & Müller, R. (2025). Impact of Biomimetic Pinna Shape Variation on Clutter Echoes: A Machine Learning Approach. *Advanced Intelligent Systems*, e202500442.

3. **Eshera, I.** & Müller, R. (2025). Machine Learning for Biosonar Systems: Investigating Dynamic Sensing in Complex Natural Environments . *Proceedings of the 42nd National Conference on Mechanical Engineering of CSME.*

4. **Eshera, I.**, Lagad, S. V., & Müller, R. (2023). Investigating the impact of biomimetic pinna shape variations on clutter echoes received from natural environments. *The Journal of the Acoustical Society of America, 154*(4_supplement), A21. **(Best Poster Award)**

5. Müller, R., Chakrabarti, S., **Eshera, I.**, Lagad, S. V., Wang, R., & Zhang, L. (2021). "Autonomy, soft-robotics, deep learning, and bat biosonar." *The Journal of the Acoustical Society of America (JASA)*, 150(4), A325-A325.

6. Lagad, S. V., **Eshera, I.**, Chakrabarti, S., & Müller, R. (2021). Development of a tension-controlled soft-robotic actuation system for a biomimetic bat robot *The Journal of the Acoustical Society of America (JASA),* 150(4), A324-A324.

Agenda

- Motivation & Prior Art
- My Contributions
  - Static Pinna Shape Conformations on Clutter Echoes
    - Methods
    - Results & Discussion
  - Dynamic Pinna Motions on Clutter Echoes
    - Modified Methods
    - Results & Discussion
- Summary & Conclusion

Agenda

- Motivation & Prior Art
- My Contributions
  - Static Pinna Shape Conformations on Clutter Echoes
    - Methods
    - Results & Discussion
  - Dynamic Pinna Motions on Clutter Echoes
    - Modified Methods
    - Results & Discussion
- Summary & Conclusion

Engineered Sonar vs. Biological Sonar

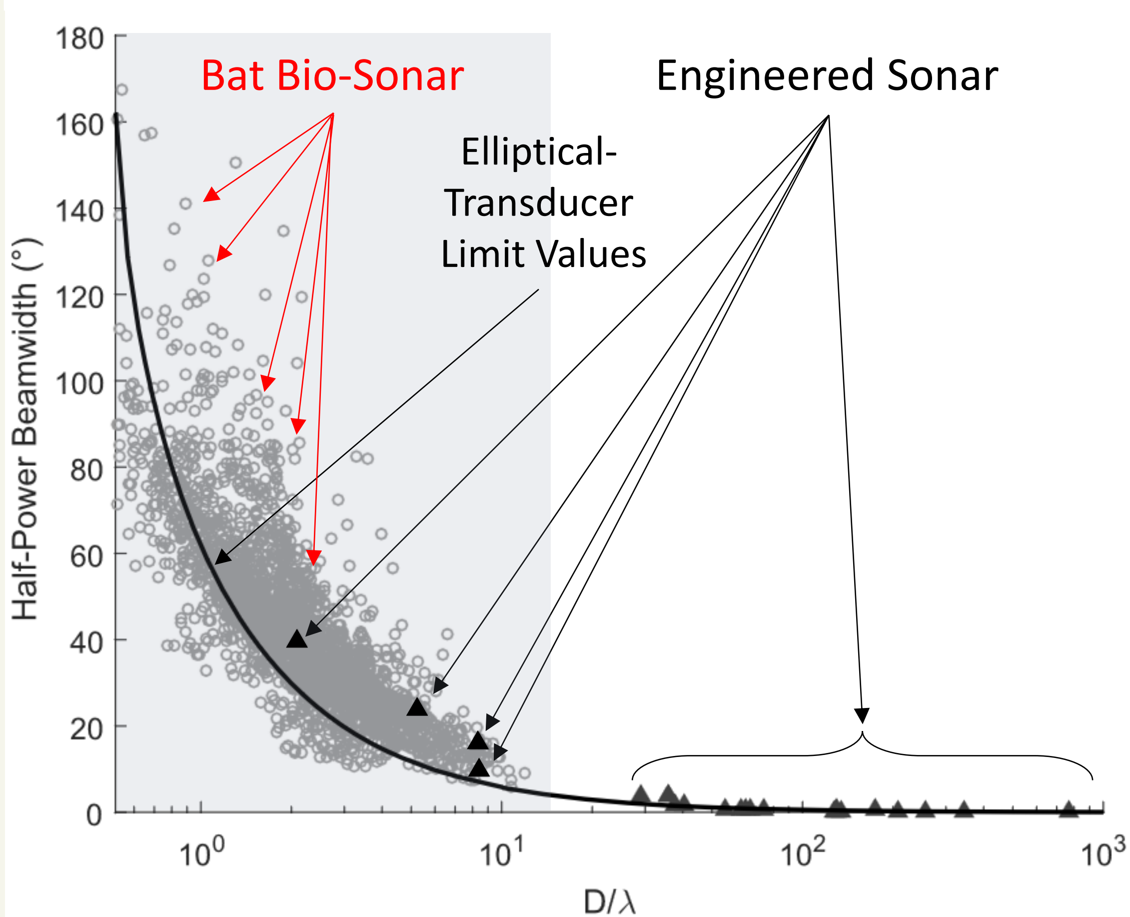
Engineered Sonar

- Designed to **minimize beamwidth** → achieve narrow, high-gain beams
- **Performance goal:** maximize angular resolution and detection range
- Follows **elliptical-transducer limit** (physics-based optimum for D/λ)

Bat Biosonar

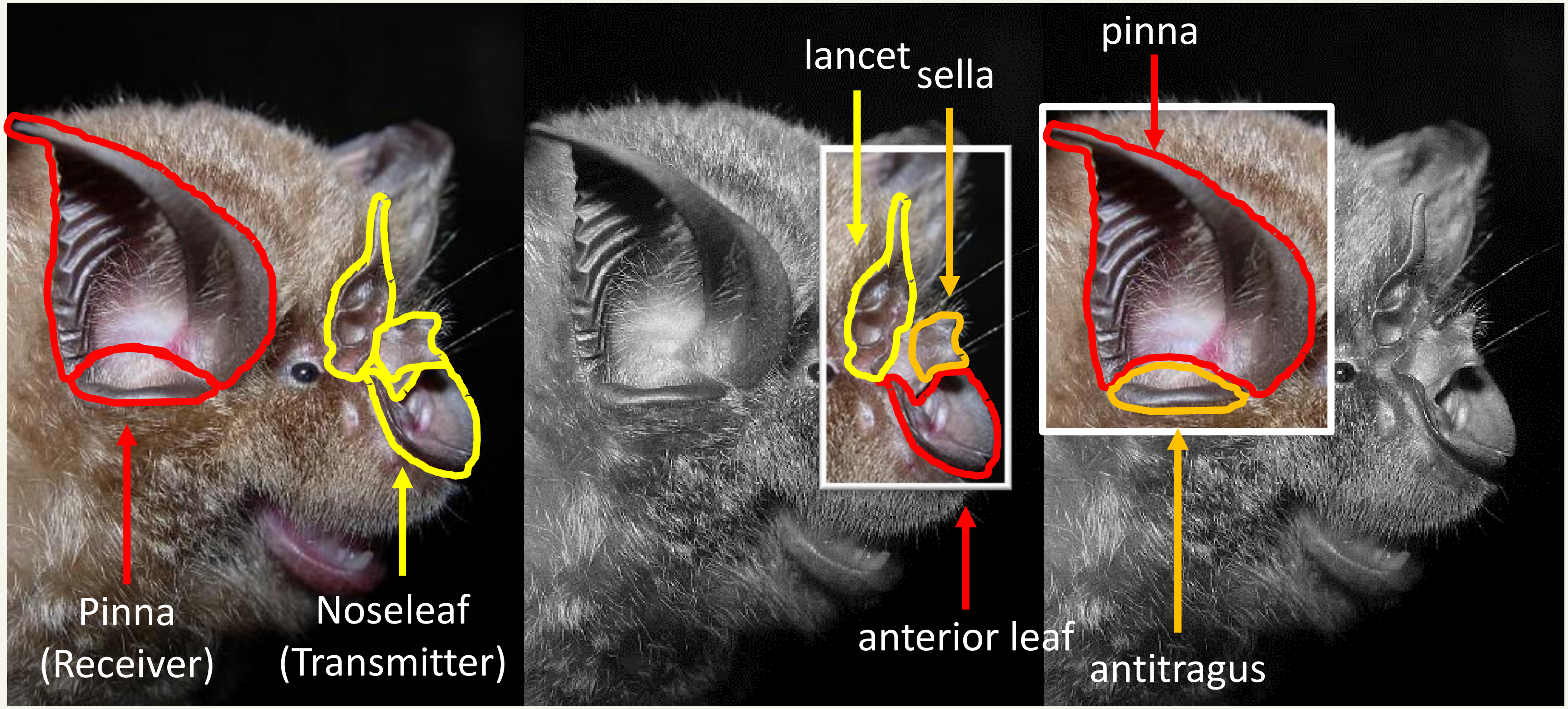
- Operates **well above** the transducer limit → intentionally broader beams
- **Does not minimize** beamwidth despite physical capacity to do so
- Exhibits **large variability** across species and frequencies
- Suggests evolution optimizes for **information richness, flexibility, and adaptability**, not geometric efficiency

Comparison of Biosonar and Engineered Sonar Half-Power Beamwidth



Todd, B. D., & Müller, R. (2018). A comparison of the role of beamwidth in biological and engineered sonar. *Bioinspiration & Biomimetics*, *13*(1), 016014. https://doi.org/10.1088/1748-3190/aa9a0f

Emission and Reception in Horseshoe Bats



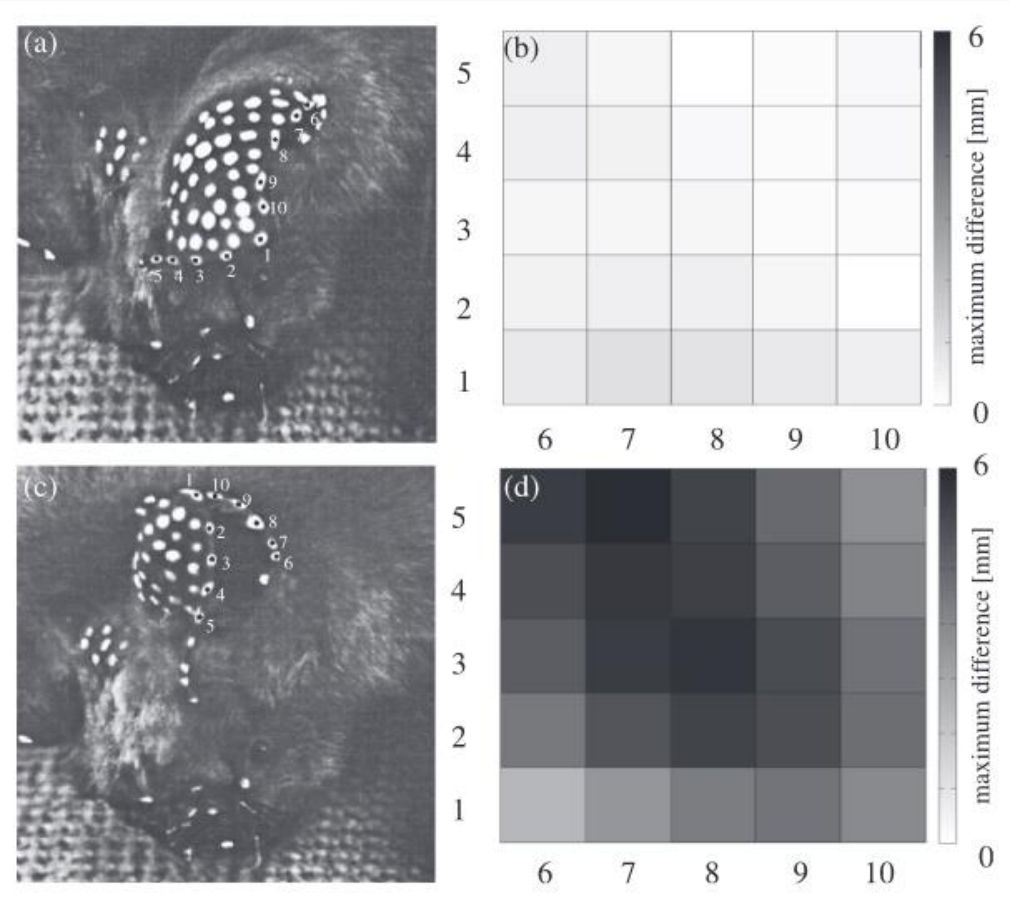
Bats Have Two Distinct Types of Pinna Motions

Rigid Rotation

- The entire ear structure rotates with respect to the head.

Non-Rigid Rotation

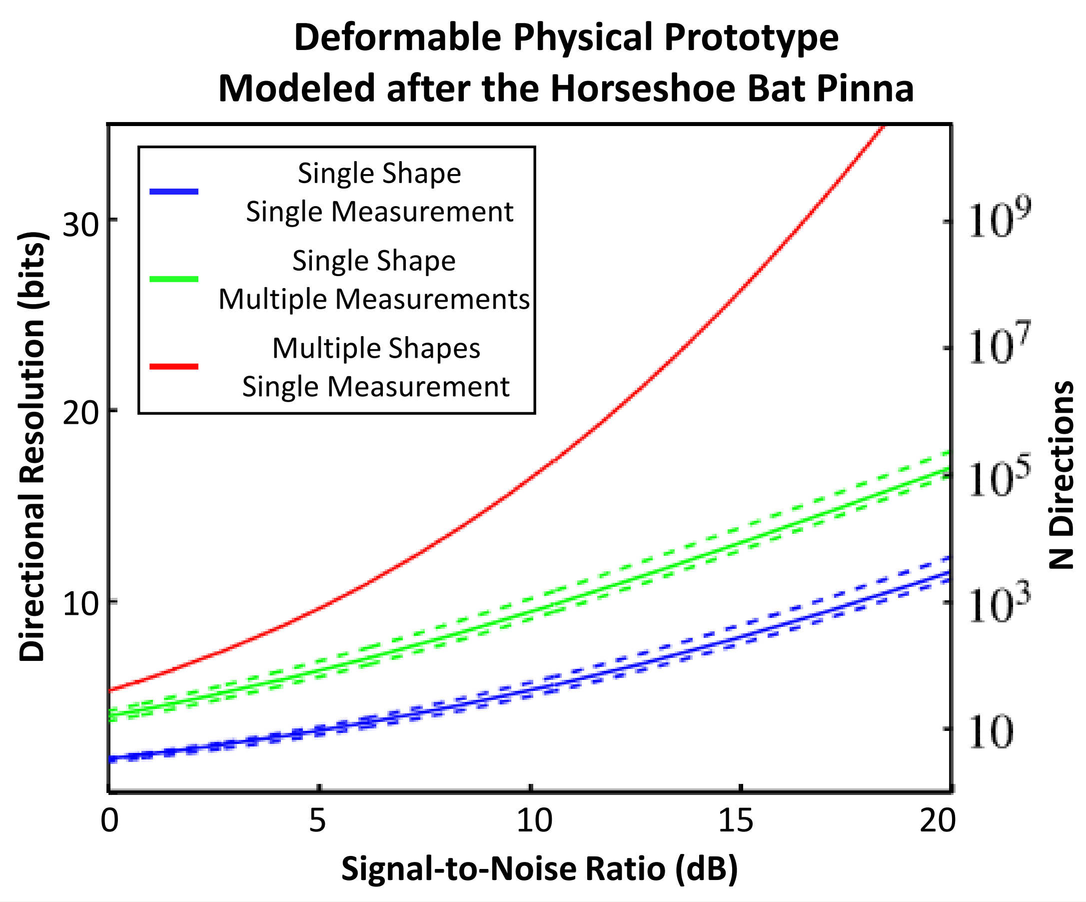
- The ear structure deforms without necessarily changing the overall structure's rotation on the head



Yin, X., Qiu, P., Yang, L., & Müller, R. (2017). Horseshoe bats and Old World leaf-nosed bats have two discrete types of pinna motions. *The Journal of the Acoustical Society of America, 141*(5), 3011-3017.

Making a Case for Non-Rigid Deformations: A Theoretical Approach

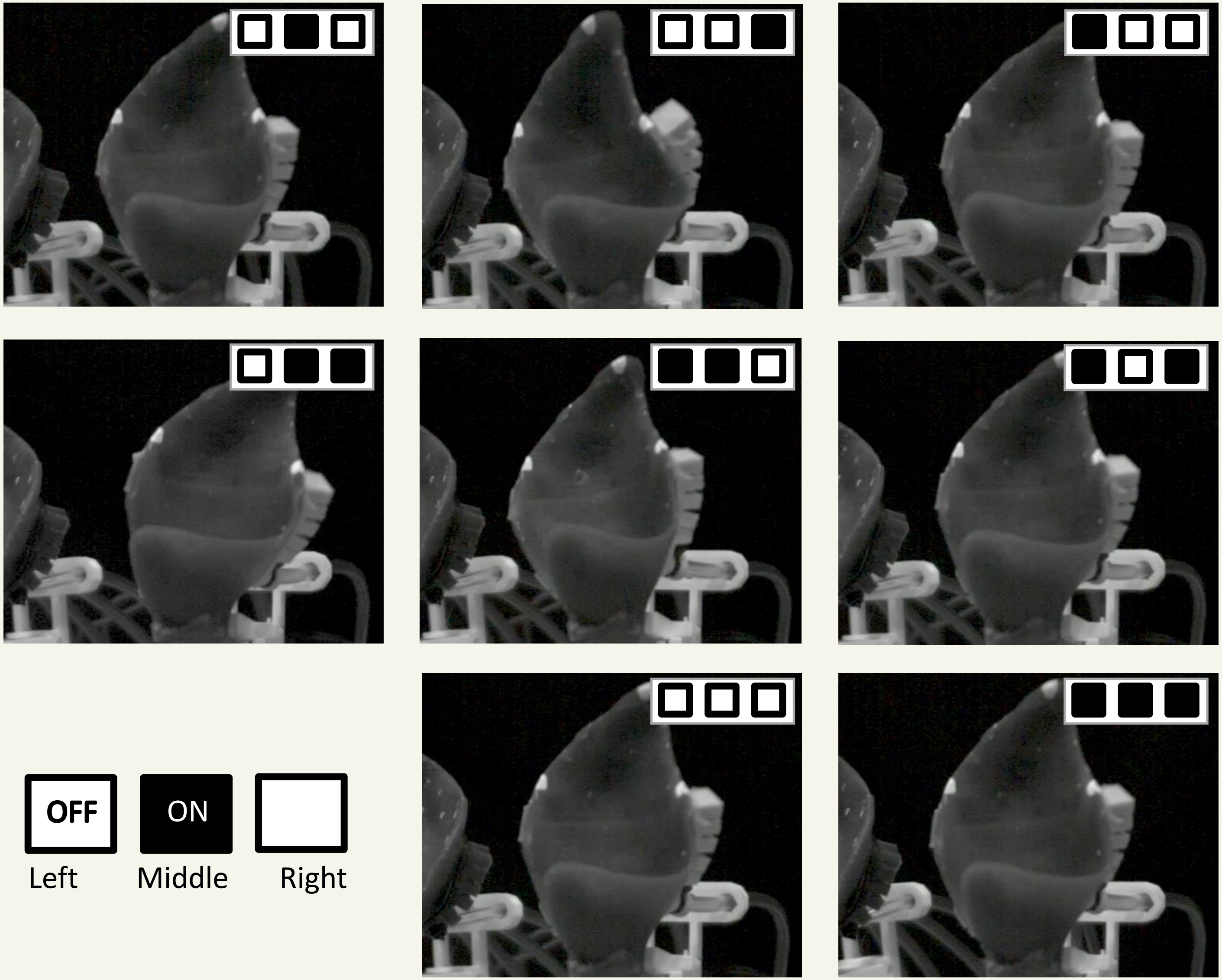
- Theoretical Study
- Including multiple pinna shapes **increases** directional resolution
- Potential advantages of multiple shape conformations established theoretically, does not present means to achieve it.



Müller, R., Gupta, A. K., Zhu, H., Pannala, M., Gillani, U. S., Fu, Y., Caspers, P., & Buck, J. R. (2017). Dynamic Substrate for the Physical Encoding of Sensory Information in Bat Biosonar. *Physical Review Letters, 118*(15), 158102. https://doi.org/10.1103/PhysRevLett.118.158102

VIRGINIA TECH.

Biomimetic Soft Robotic Pinna



My Contribution: Is There a Consistent Effect

- **Motivation:**
  - Different pinna conformations (static & dynamic) impart distinct acoustic cues about the environment; Machine Learning might be able to extract this information.
- **Hypothesis:**
  - Ear shape deformation introduces consistent, shape-specific changes in the received echo signals which are detectable across repeated trials in clutter.
    - H_0: Pinna deformation has **no consistent effect** on clutter echoes; any observed differences are due to chance.
    - H_1: Pinna deformation has **a consistent** and detectable effect on clutter echoes.
- **Implication:**
  - If H_1 holds → deformation contributes to *adaptive sensing* and enhances clutter discrimination.
  - If H_0 holds → peripheral ear motion has *no functional role* in biosonar information processing.

Novel Hardware & Software Pipeline

Novel Lab Data Collection Setup	Raw Signal Data	DSP Techniques	Machine Learning Classification Problem
Ten Discrete **Static** Pinna Conformations + Foliage	FM	Spectrogram	CNN, ResNet
Ten **Dynamic** Pinna Deformation Motions + Foliage	CF, FM, CF-FM	Spectrogram	CNN, Transformers, ResNet, Unsupervised Learning & Clustering

Problem Statement 1: Static Pinna Conformations on Clutter Echoes

Investigate how different static ear shapes influence the structure of clutter echoes and whether these shape-dependent effects produce distinct, classifiable acoustic signatures.

Problem Statement 2: Dynamic Pinna Motions on Clutter Echoes

Examine how *time-varying ear deformations* during echo reception alter the returning clutter signals and whether these motion-induced Doppler effects can be reliably detected and classified.

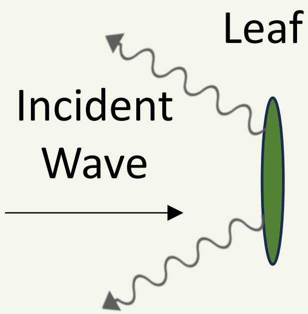
Data Collection Setup: What is the Nature of Foliage?

Leaves Are Modeled as Discs:

- Leaves are on the same scale as ultrasound wavelengths
- Modeled as thin, rigid surfaces → disc model (circular reflectors).

Disc Parameters (per leaf):

- **Radius** → size
- **Position** → range
- **Orientation** → backscattering strength (affects $\sigma(\theta)$)



Backscattered Power per Disc:

$$P_r = P_t \frac{\sigma(\theta)}{(4\pi r^2)^2} e^{-2\alpha(f)r}$$

Term	Description	Note
P_t	Transmit Power	–
$\sigma(\theta)$	Backscattering Cross-Section	Orientation Dependent
r	Range to Disc (e.g. leaf)	–
$\alpha(f)$	Medium Absorption Coefficient	Frequency Dependent

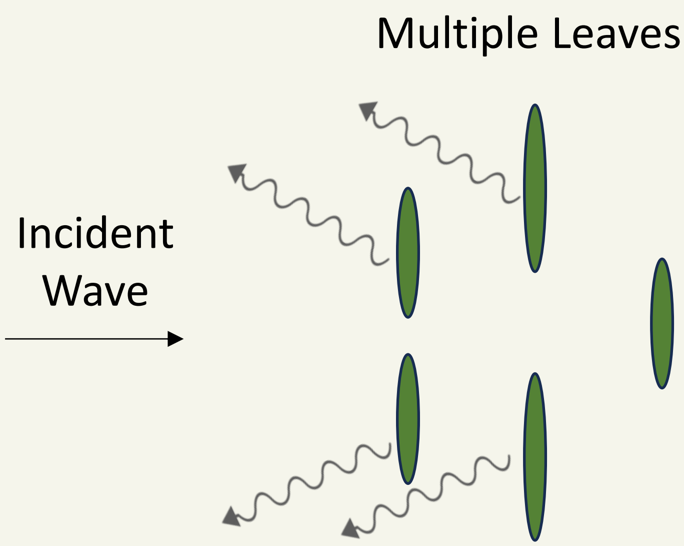
What is Clutter?

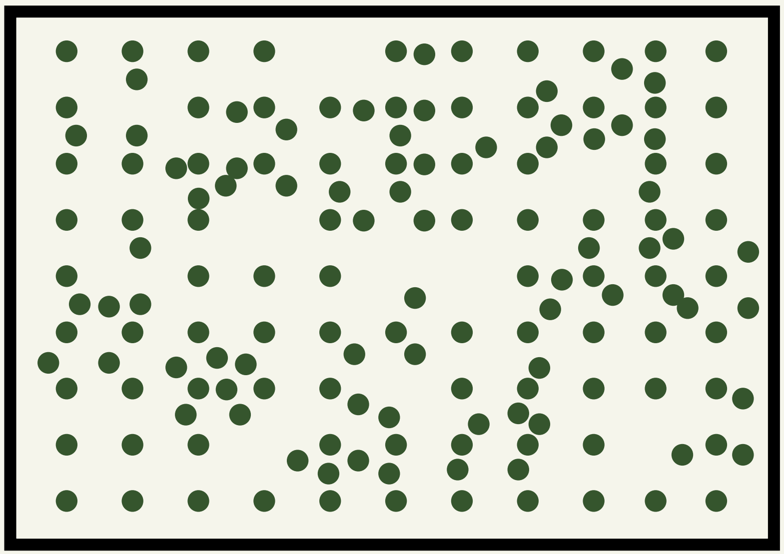
N here is very large, i.e., thousands, hundreds of thousands

For Multiple Leaves
The Total Received Echo from Foliage
(sum of N leaf returns):

$$P_r = \sum_{i=1}^{N} P_t \frac{\sigma_i(\theta_i)}{\left(4\pi r_i^2\right)^2} e^{-2\alpha(f) r_i}$$

- Each individual leaf return is weak.
- Positions r_i and orientations θ_i are random and time-varying.
- Together these contributions form a diffuse, noisy, temporally extended echo → clutter.



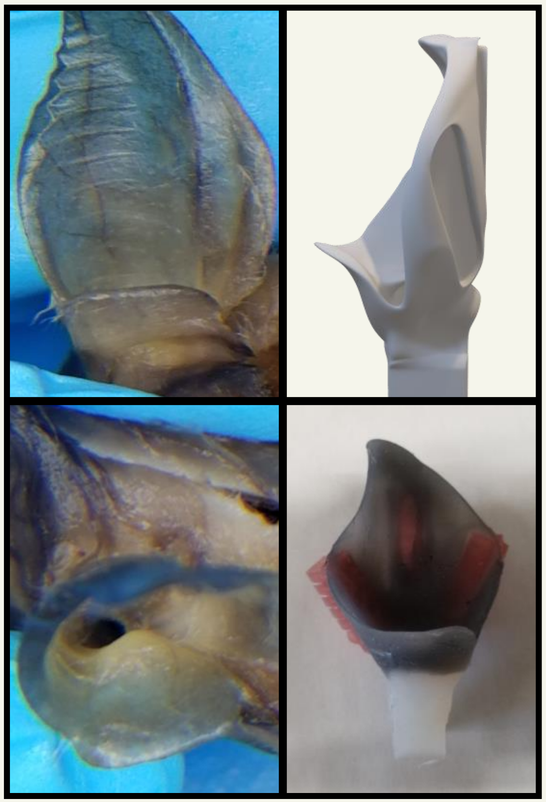


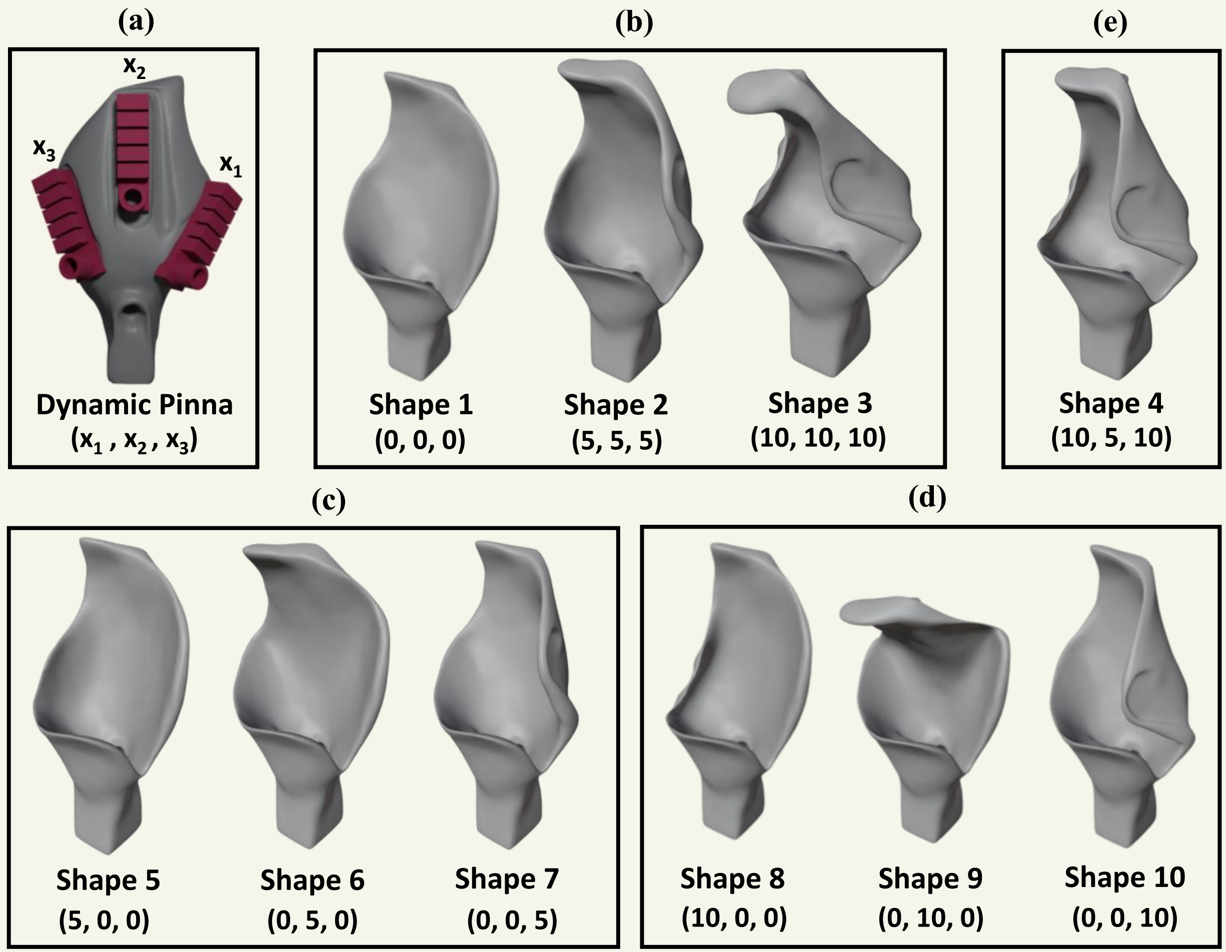
Novel Lab Data Collection Setup

Agenda

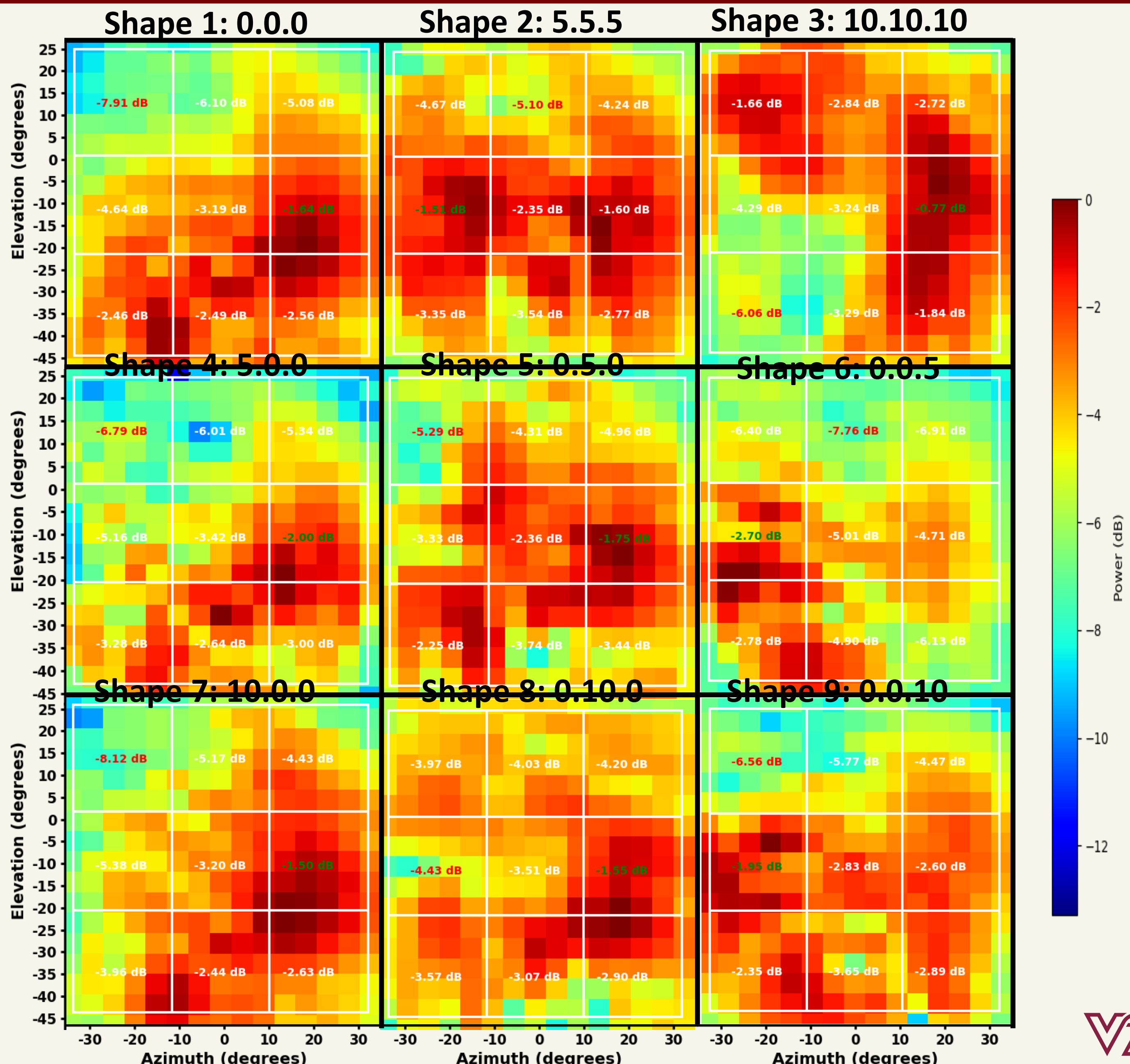
- Motivation & Prior Art
- My Contributions
  - Static Pinna Shape Conformations on Clutter Echoes
    - Methods
    - Results & Discussion
  - Dynamic Pinna Motions on Clutter Echoes
    - Modified Methods
    - Results & Discussion
- Summary & Conclusion

Pinna Model of the Study for Static Experiments





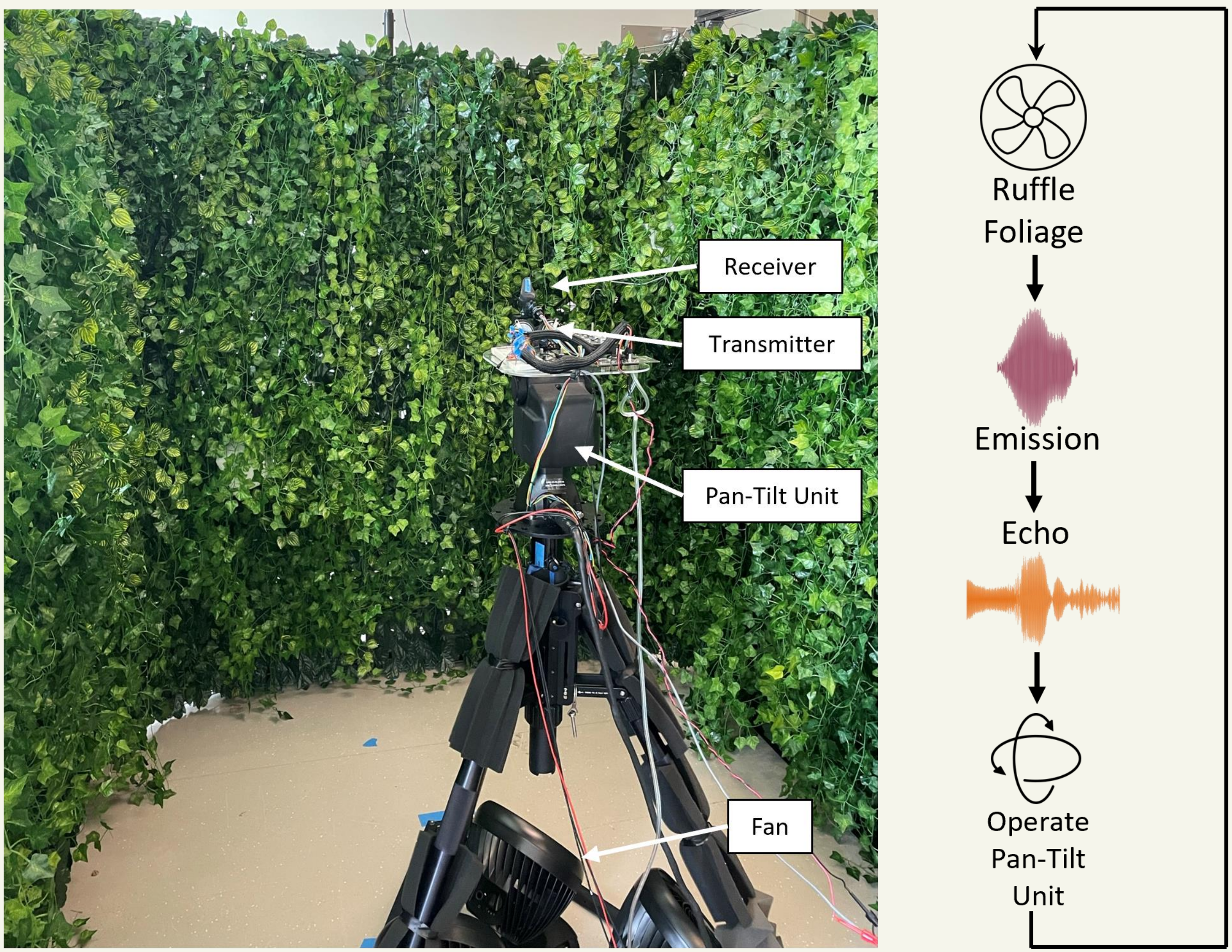
Receiver Characteristics, Example Beampatterns



VIRGINIA TECH

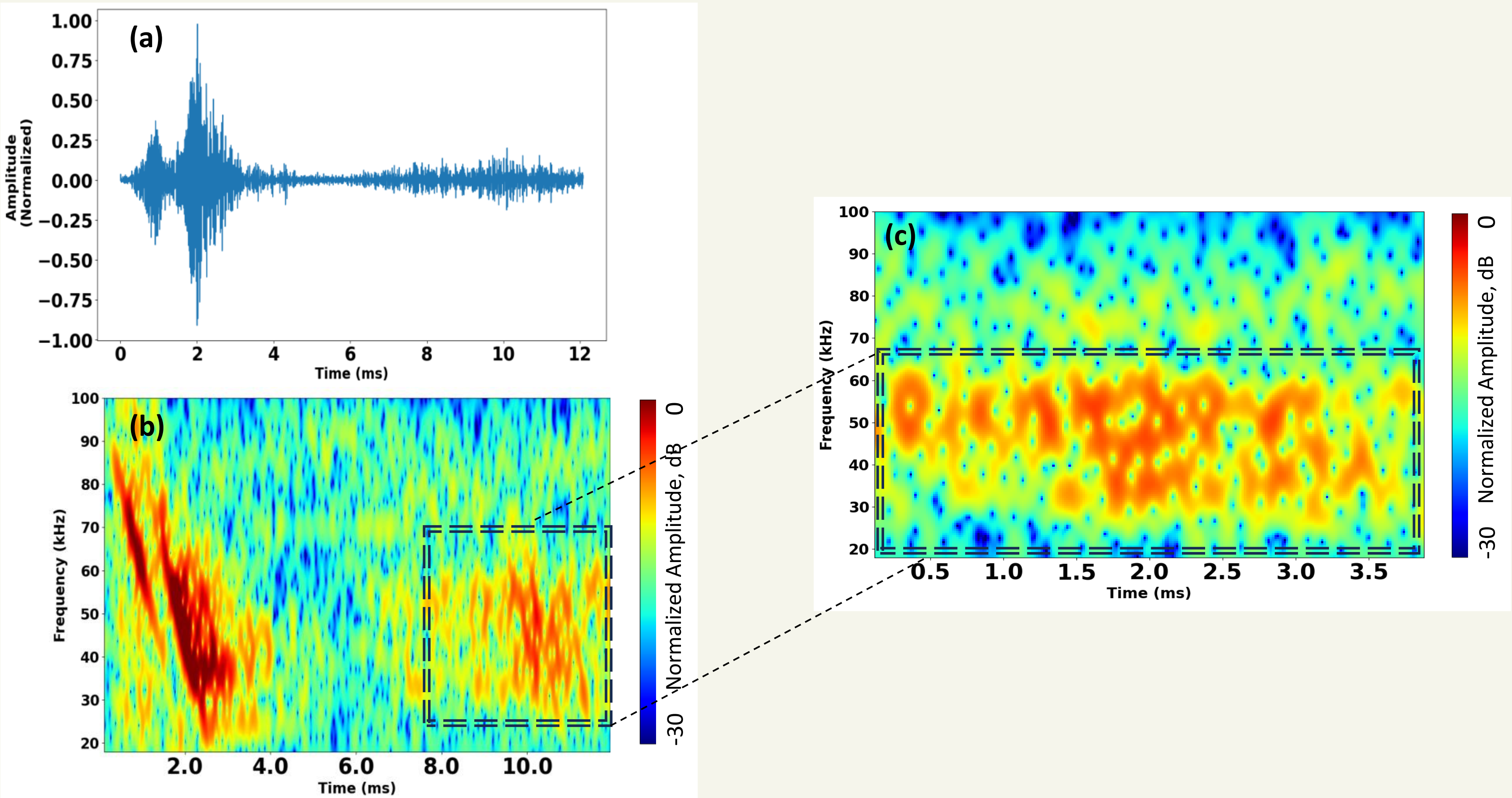
Dedicated Laboratory Setup & Control Scheme

(a) (b)

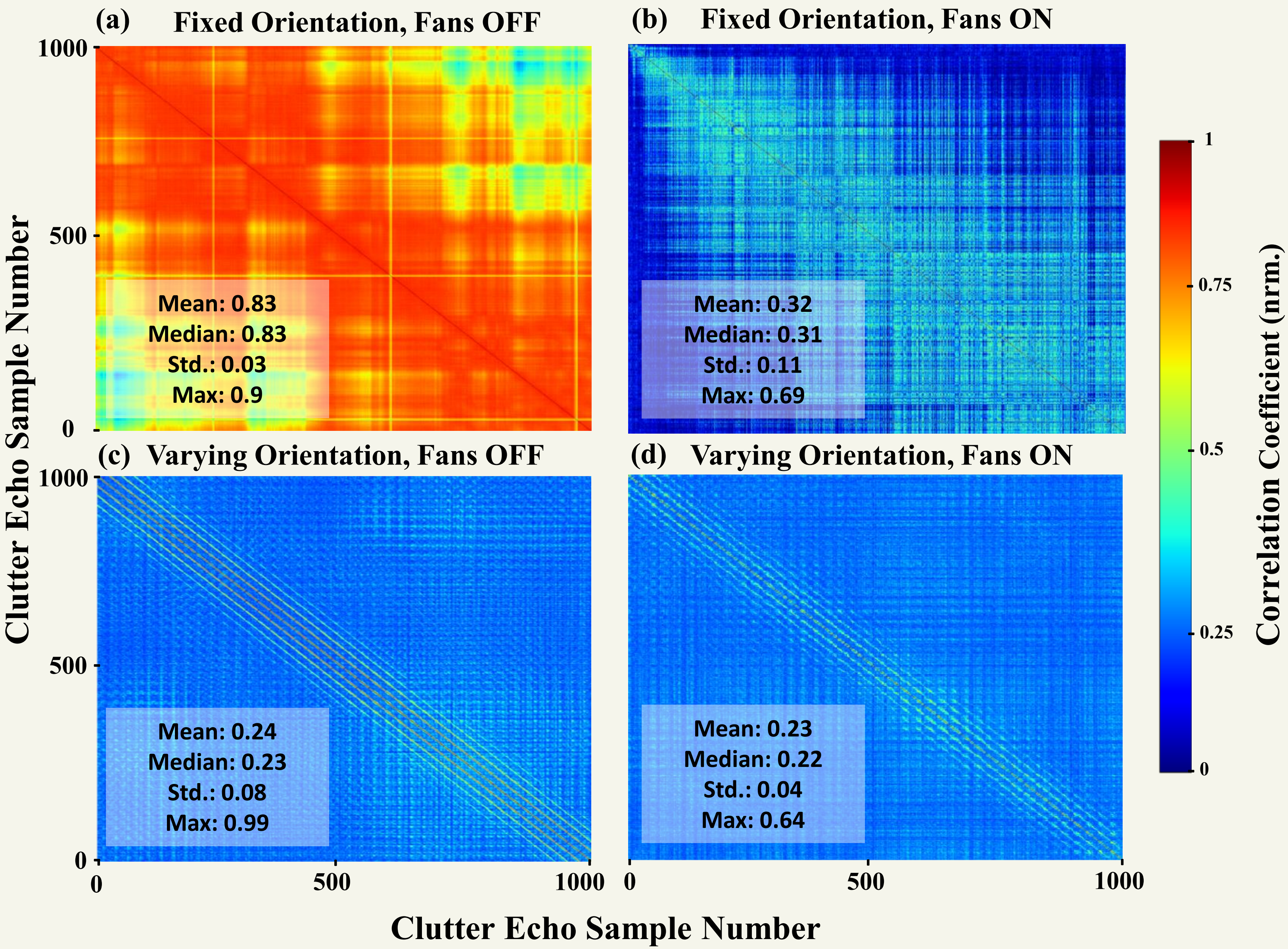


VIRGINIA TECH.

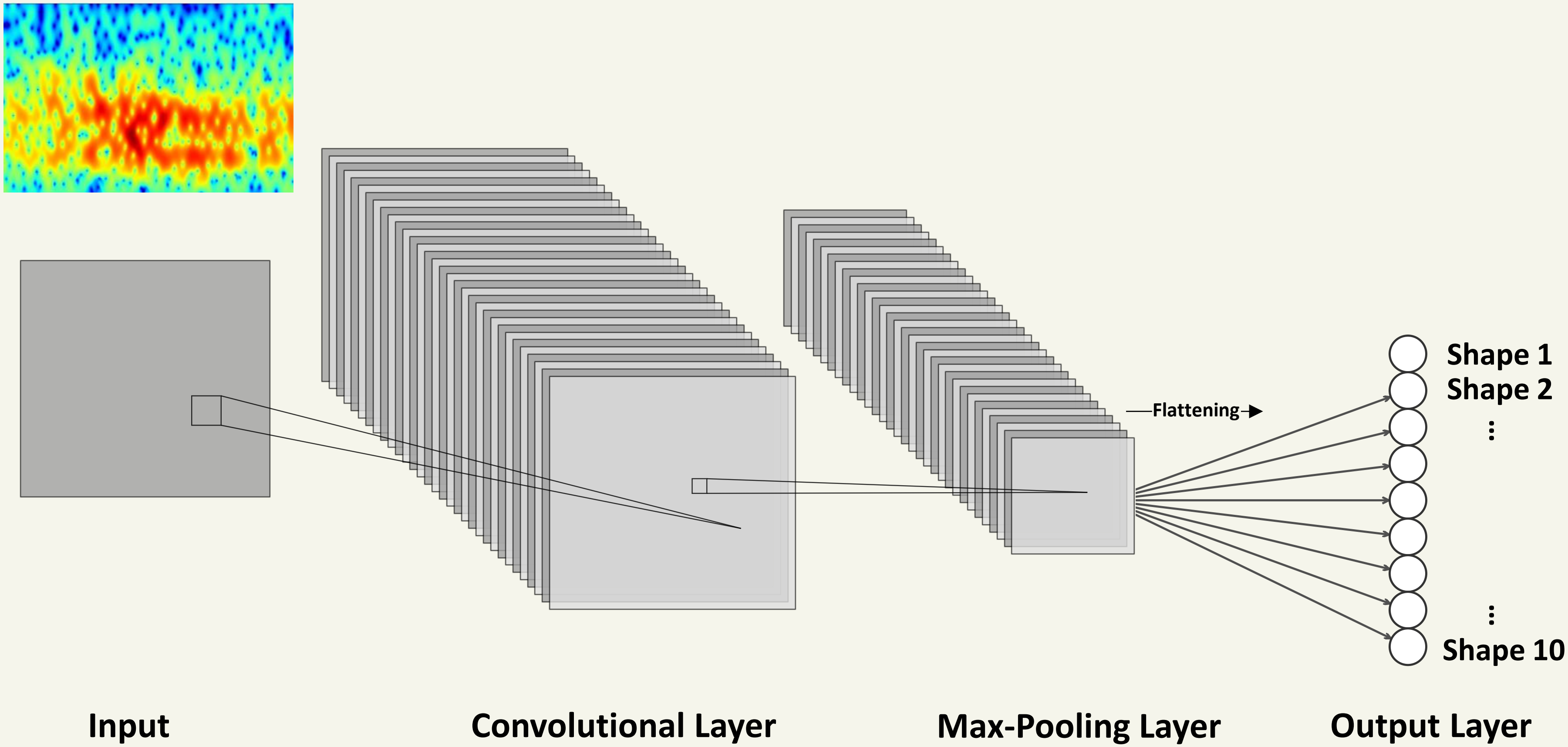
Example of the Received Signal



Correlation Matrix of Laboratory Setup

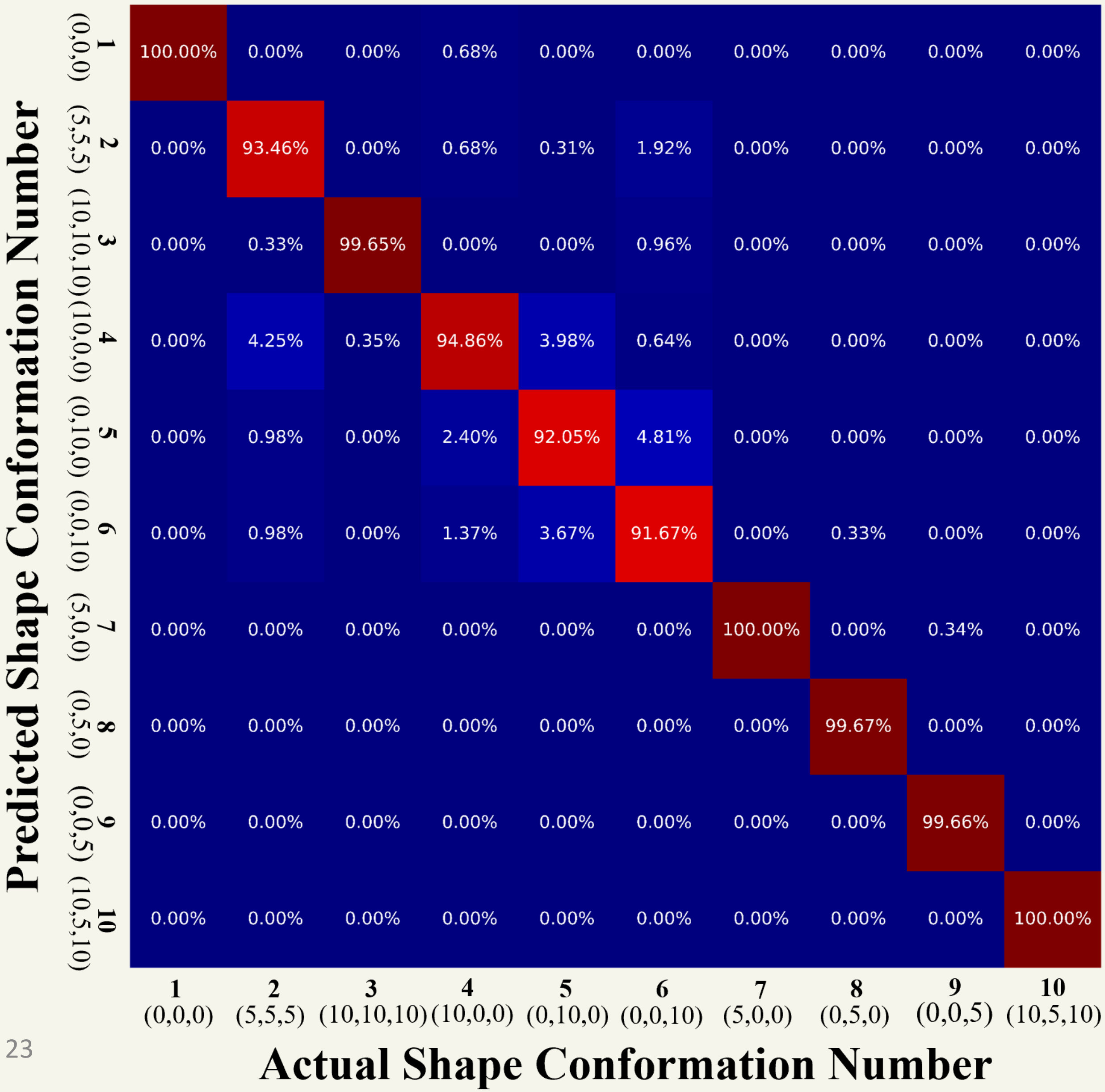


CNN Architecture



VIRGINIA TECH

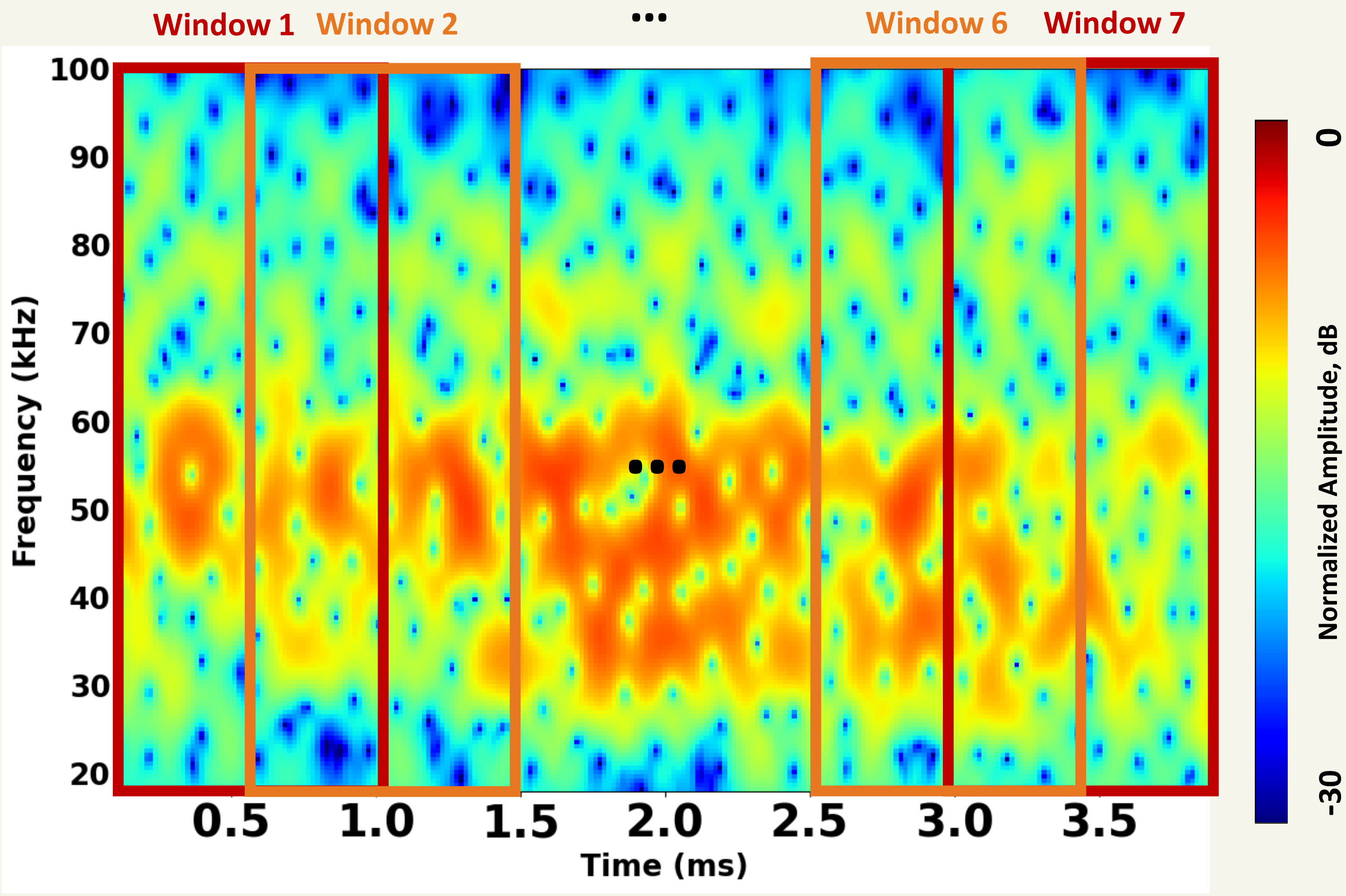
Confusion Matrix of Best-Performing Network



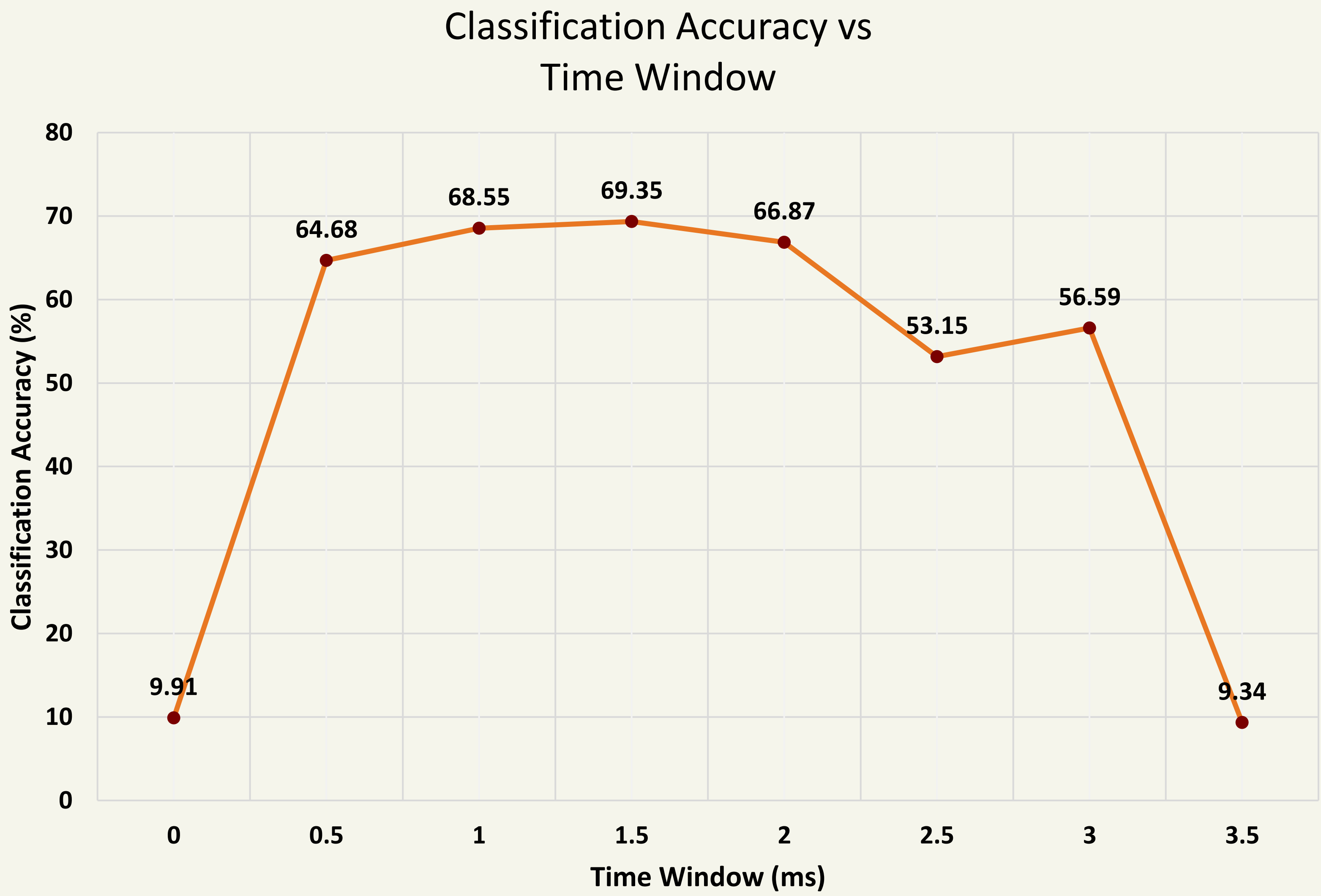
- ~1,500 echoes/class
- Train-Test-Validation Split:
  - 60%-20%-20%
  - 900-300-300
- Test is unseen to network
- 97.8% Overall Accuracy

VIRGINIA TECH.

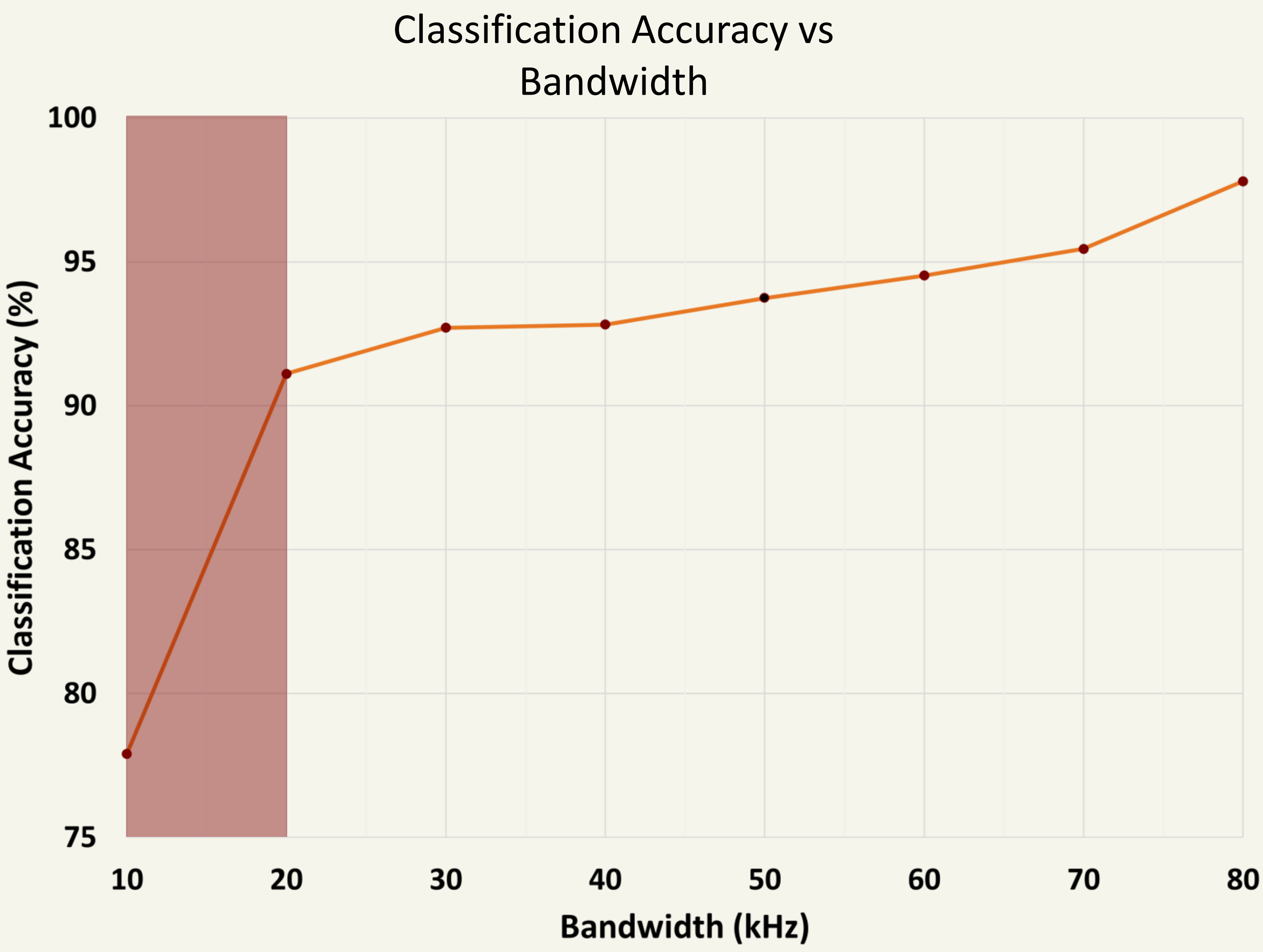
Does a certain part of the received signal contain the answer?



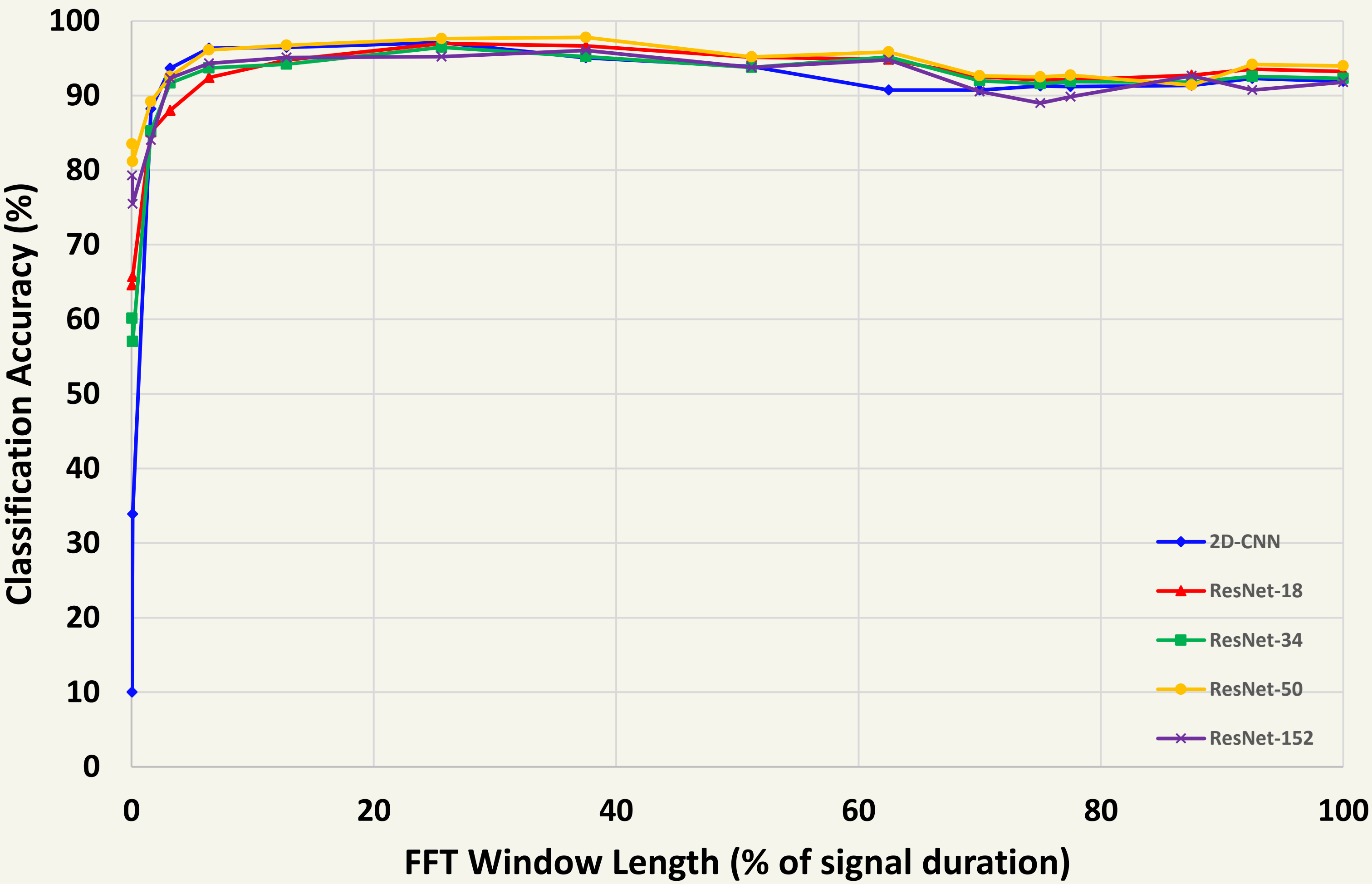
Does a certain part of the received signal contain the answer?



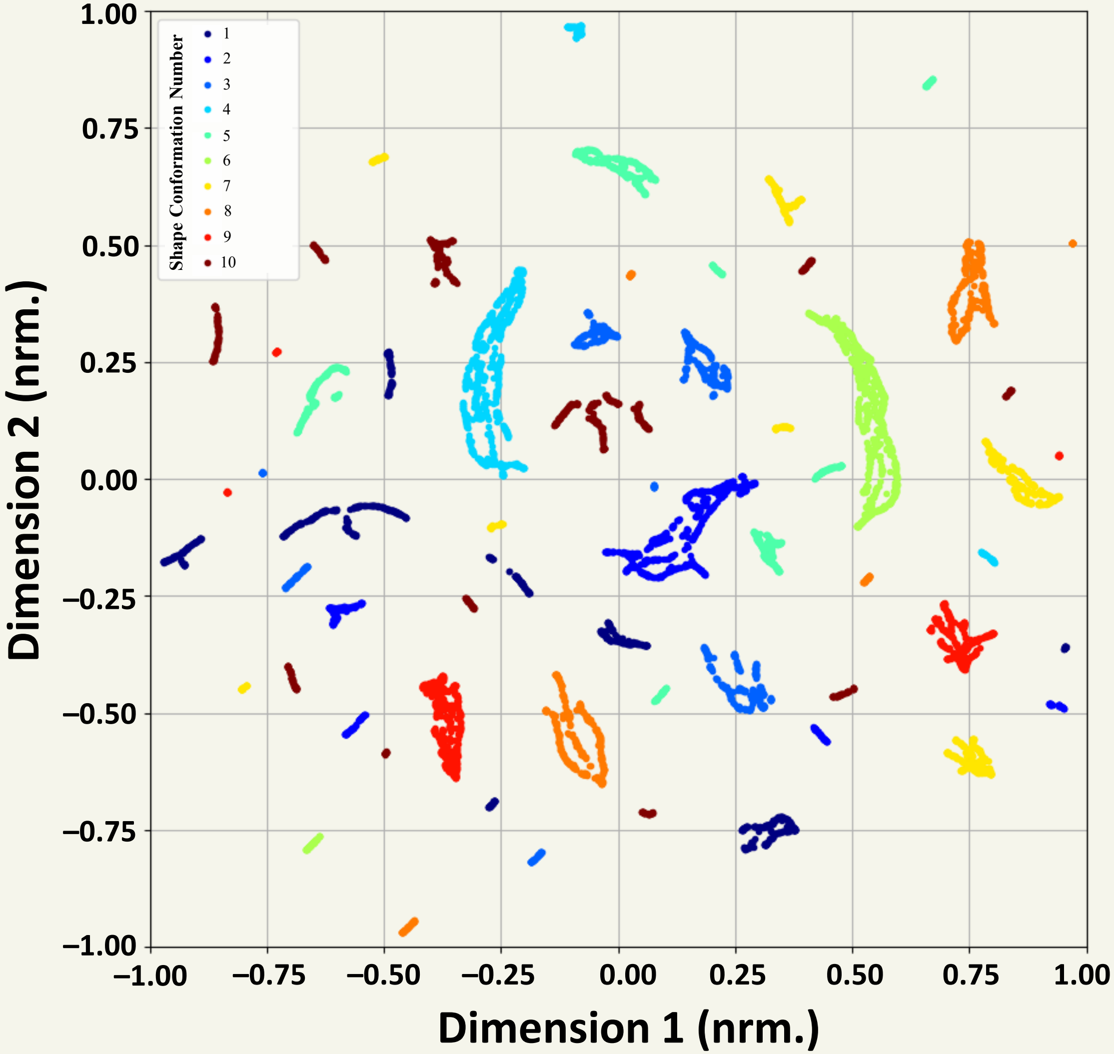
Does Bandwidth Have An Impact?



Time-Frequency Parameters



2-D Separability Analysis on Final Layer



Discussion & Informing the Coming Work

- Bats may leverage the clutters variability to encode additional sensory dimensions.
- The results highlight the impact of biomimetic pinna shape variations on clutter echoes, even in highly random environments.
- Deep learning classifiers as a possible solution to extract relevant information from clutter echoes
- This information may impart well-defined acoustic cues on the received signal for each shape.
- The consistency in the information extracted despite the variability in the environment may be essential for understanding the potential sensory benefits of pinna dynamics in complex biosonar tasks.
- Further work can explore downstream sensory-specific tasks taking advantage of different shape deformations.

Published Work:

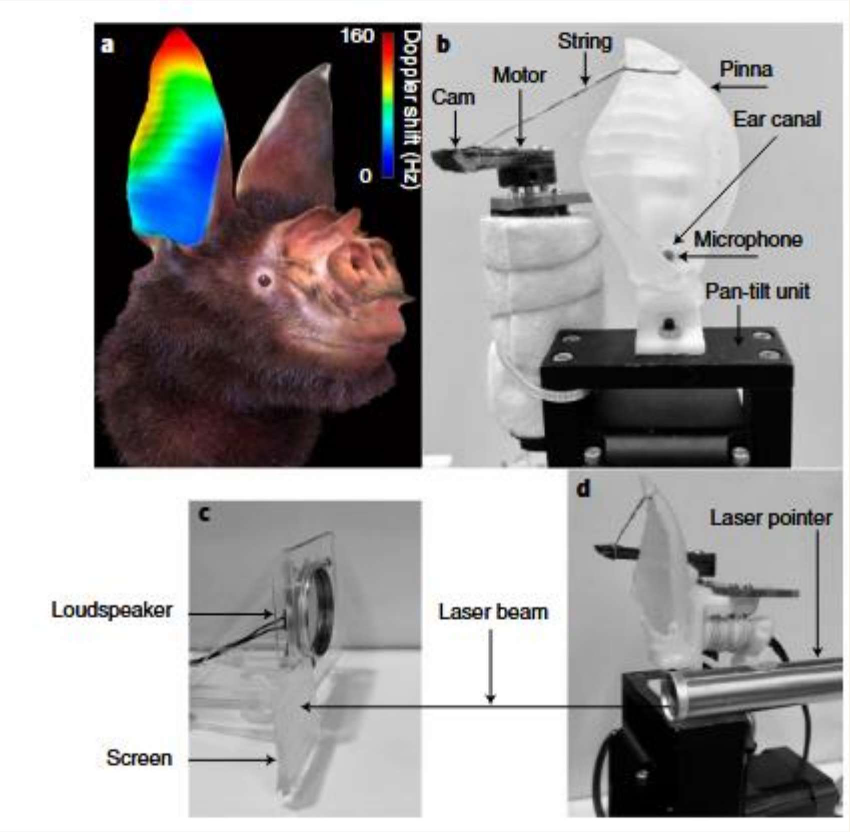
Eshera, I., Lagad, S., & Müller, R. (2025). Impact of Biomimetic Pinna Shape Variation on Clutter Echoes: A Machine Learning Approach. *Advanced Intelligent Systems*, e202500442.

Agenda

- Motivation & Prior Art
- My Contributions
  - Static Pinna Shape Conformations on Clutter Echoes
    - Methods
    - Results & Discussion
  - Dynamic Pinna Motions on Clutter Echoes
    - Modified Methods
    - Results & Discussion
- Summary & Conclusion

Exploring The Non-Linear Aspect of Deformations

- Prior work demonstrated that Doppler signatures induced by deforming pinnae encode directional information with sub-degree precision.
- These signatures emerge even when the source is stationary, validating the idea that receiver motion alone can introduce useful Doppler structure.
- Can we use this in clutter as well?

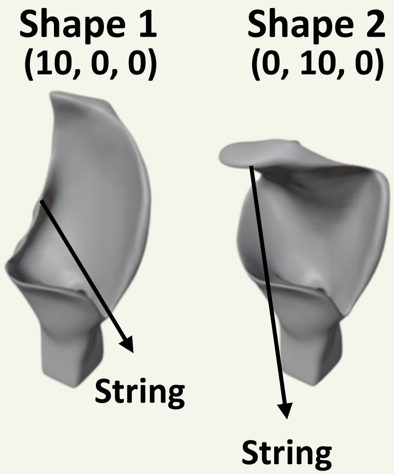


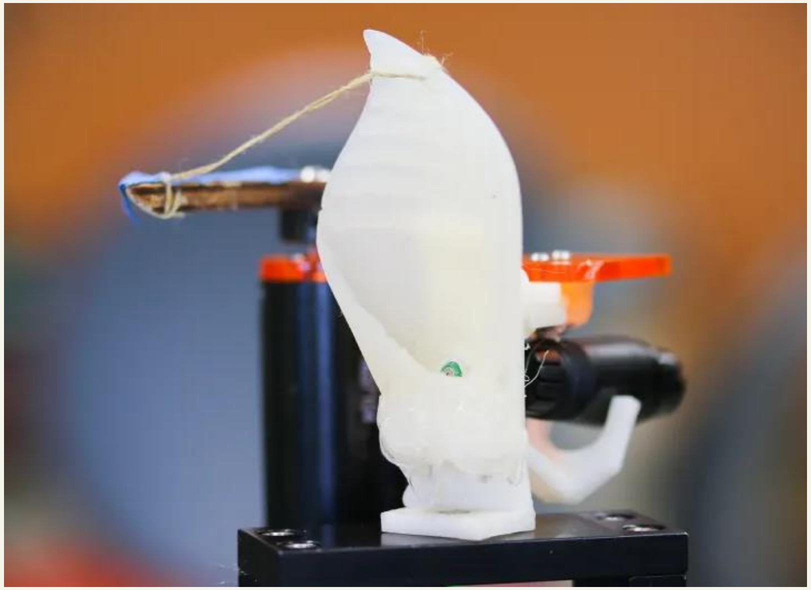
Exploring The Non-Linear Aspect of Deformations

VIRGINIA TECH

Non-Linear Effects of Deforming in Clutter: Doppler

- Can **actively** deforming a biomimetic ear encode useful and learnable structure in echoes that pass through natural clutter?
- This would explore aspects of:
  - How form and motion work together in sensing systems
  - How information gets injected, filtered, or amplified through geometry + time dynamics
- Bats may not just passively receive sensory signals, they may shape them through motion (ear twitches, etc.)
- This experiment probes whether these movements inject discriminative features into the signal.

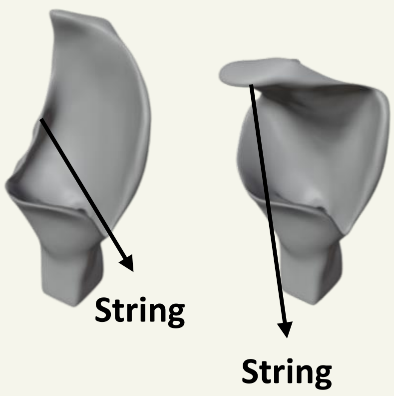




Designing an Experiment

Shapes

- Deformation to Create Shape 1 (Sidewards Pull)
- Deformation to Create Shape 2 (Downwards Pull)

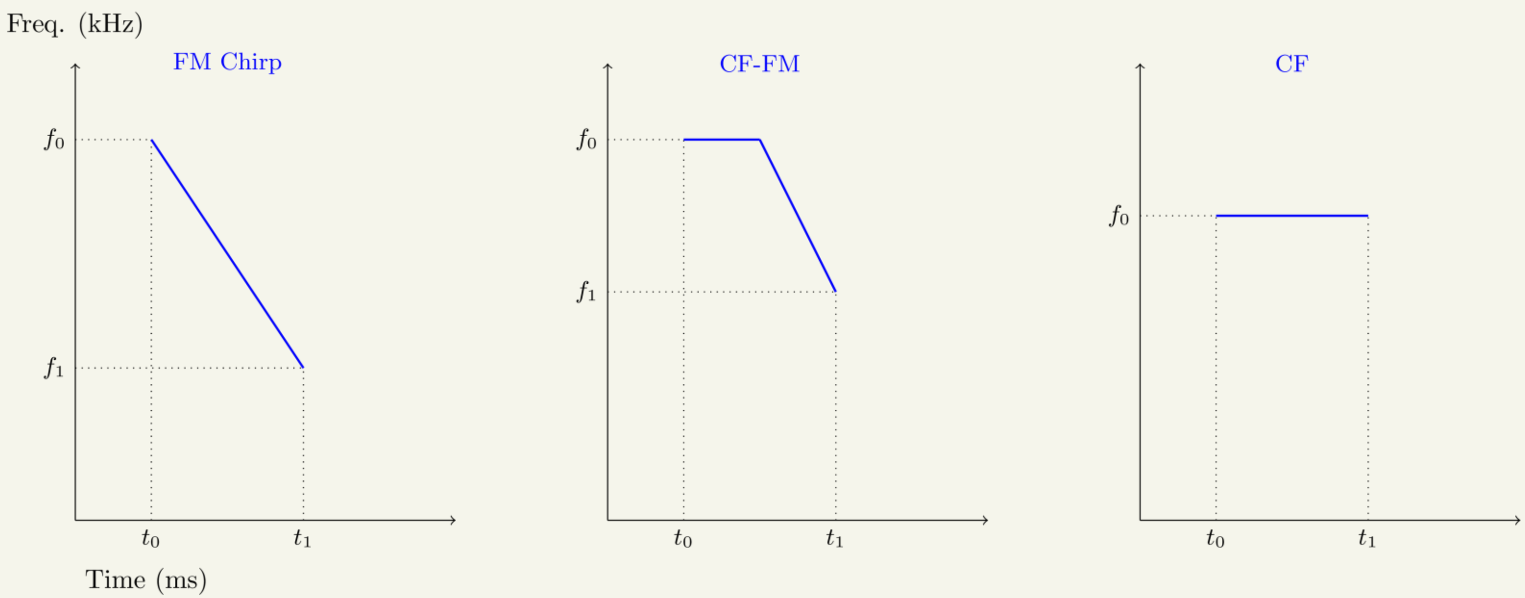


Deformation Speeds

- 20% Speed Deformation
- 40% Speed Deformation
- 60% Speed Deformation
- 80% Speed Deformation
- 100% Speed Deformation

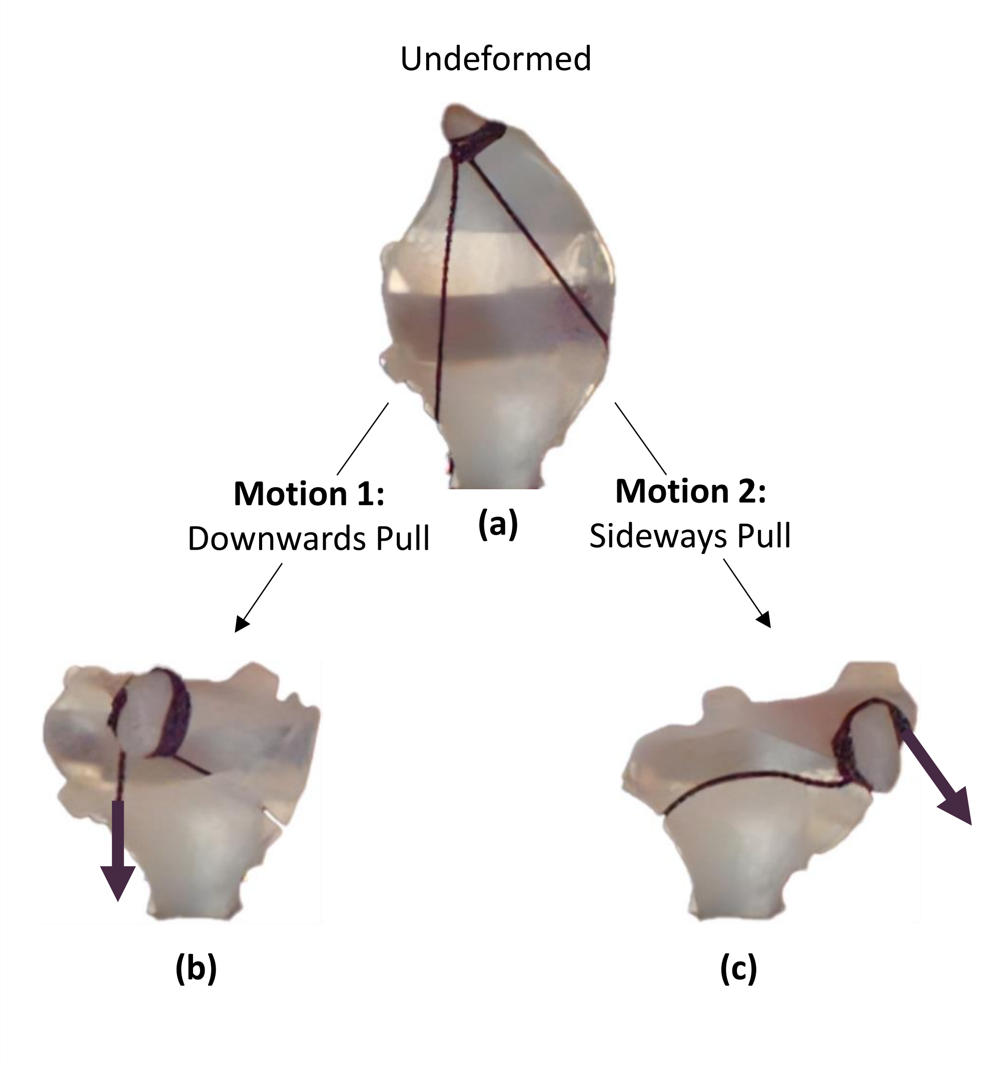
Transmit Signals

- CF
- FM
- CF-FM



VIRGINIA TECH

Doppler Motion Examples

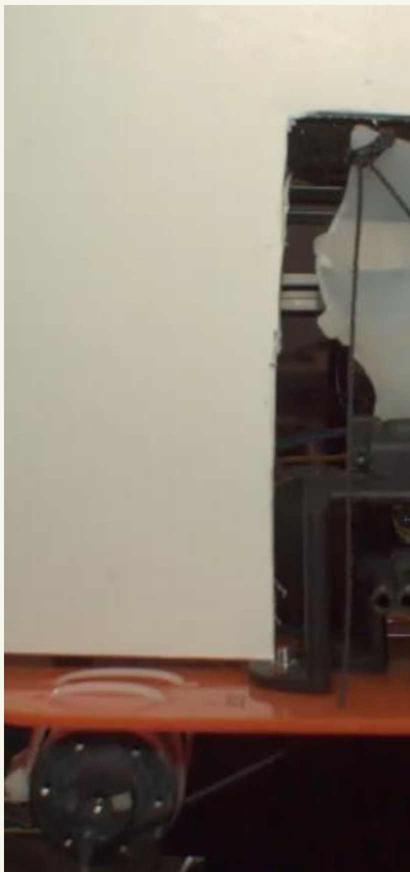


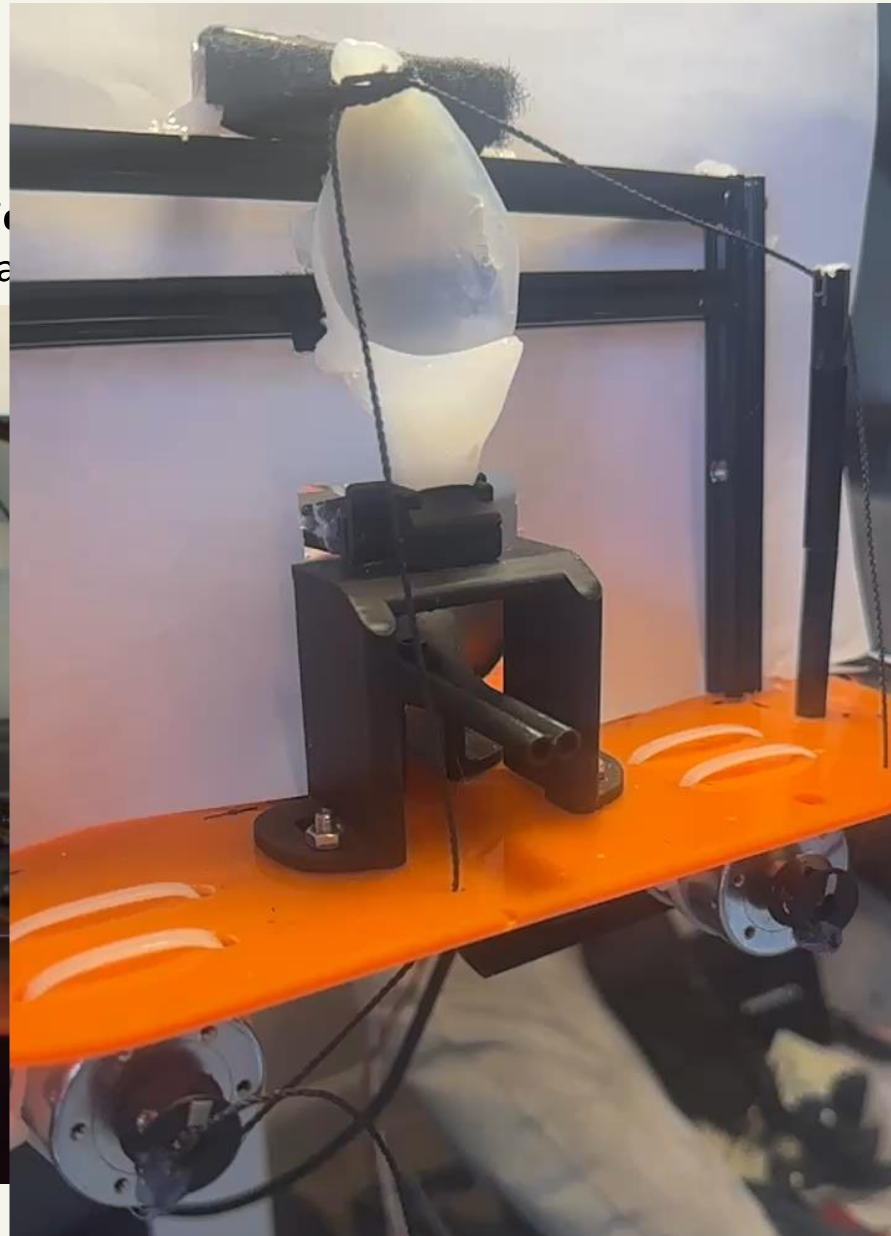
Doppler Motion Examples

Frame Rate: 1,000 fps

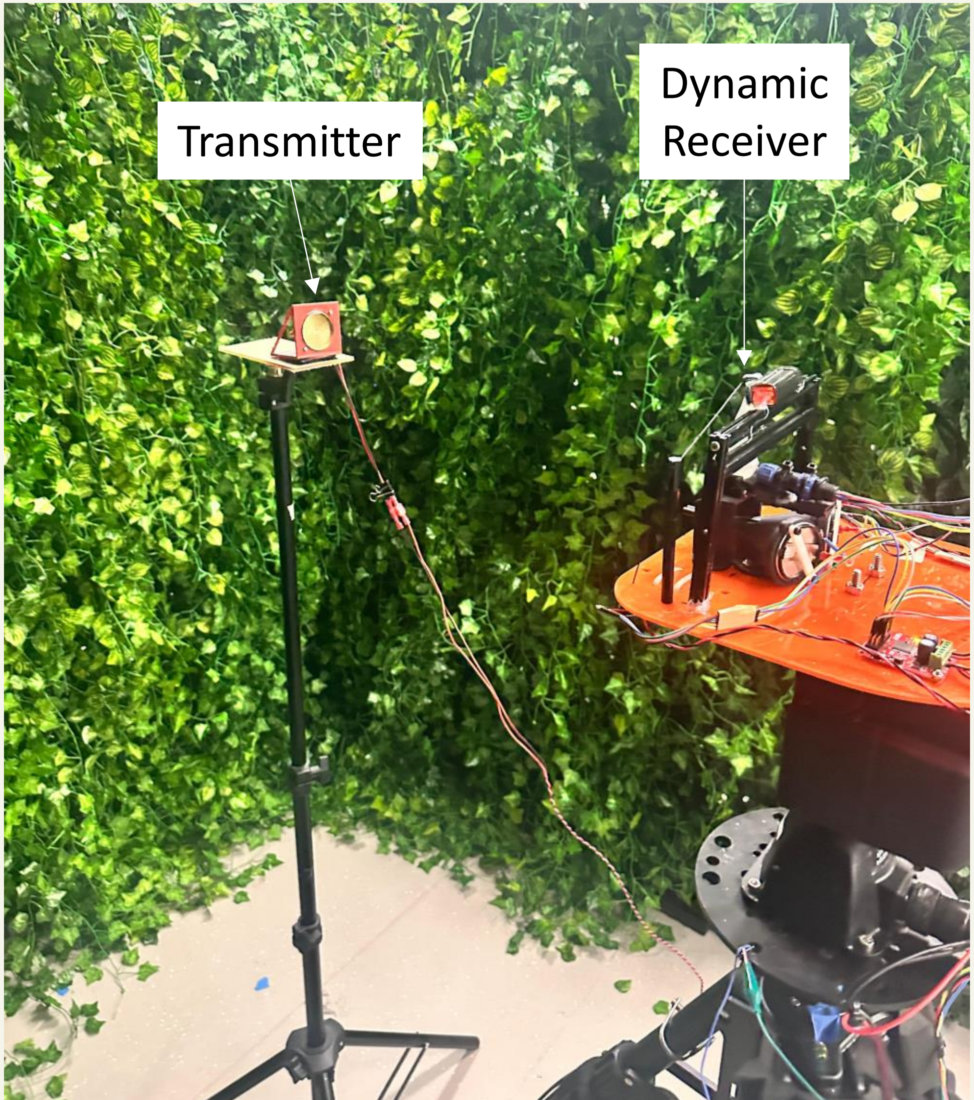
Moti **tion 2:**

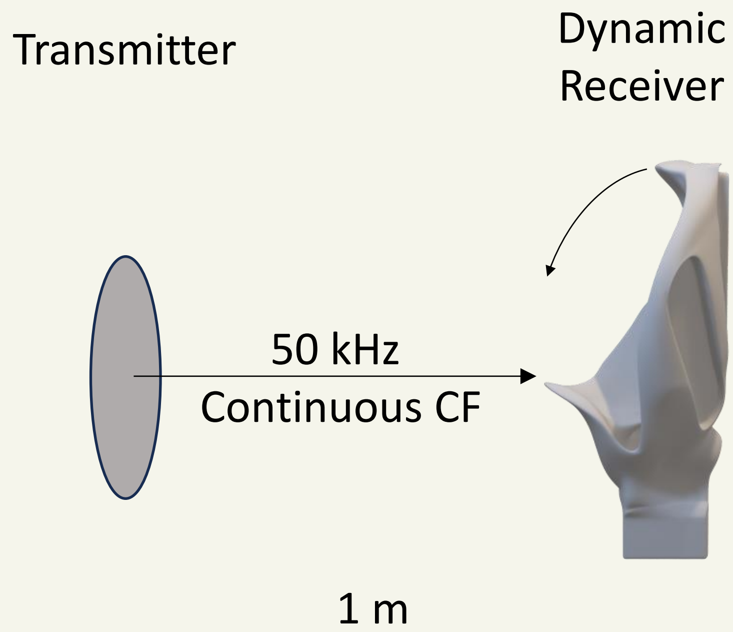
Downwa ays Pull





Doppler Characterization Setup

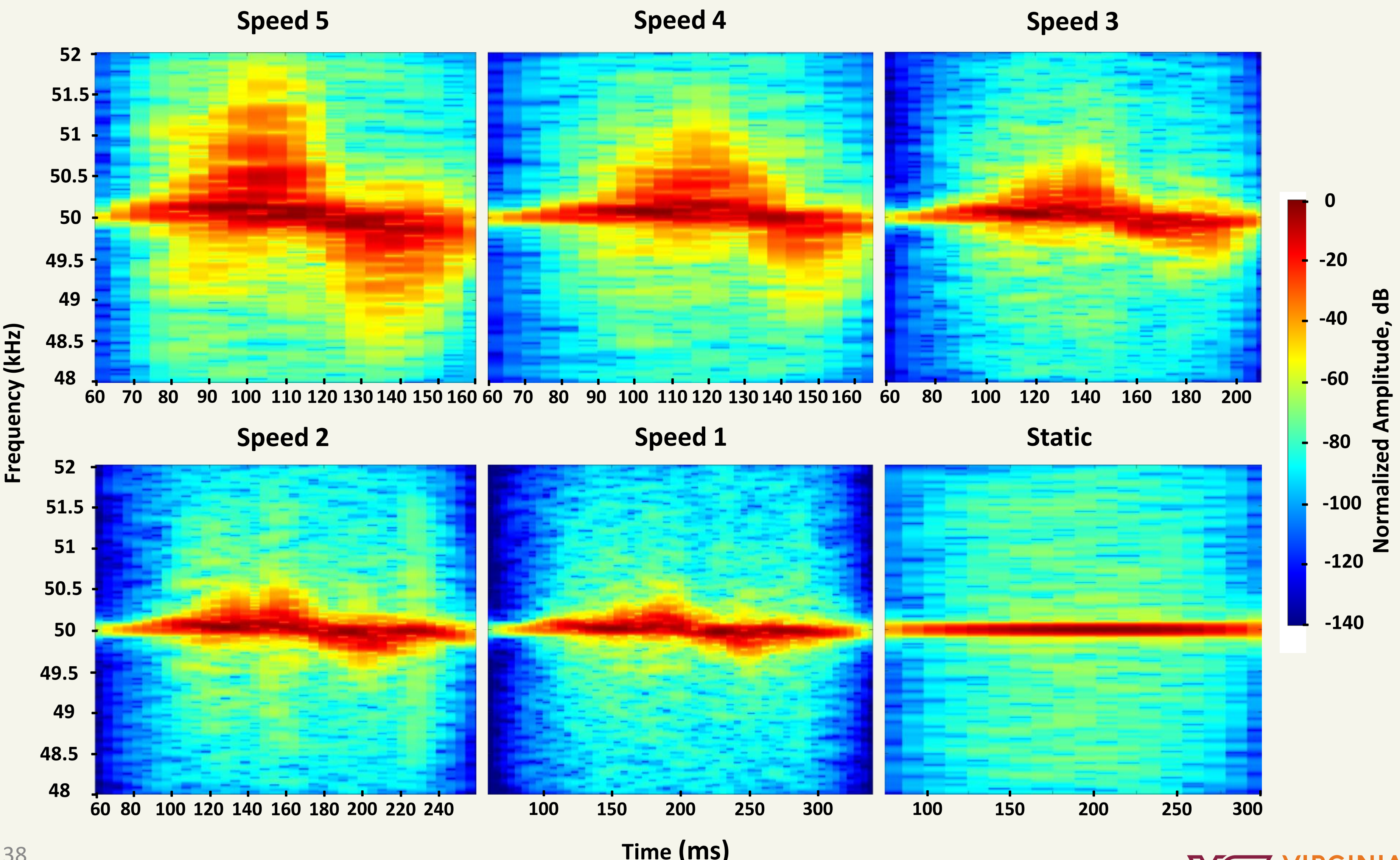




Farfield Distance:

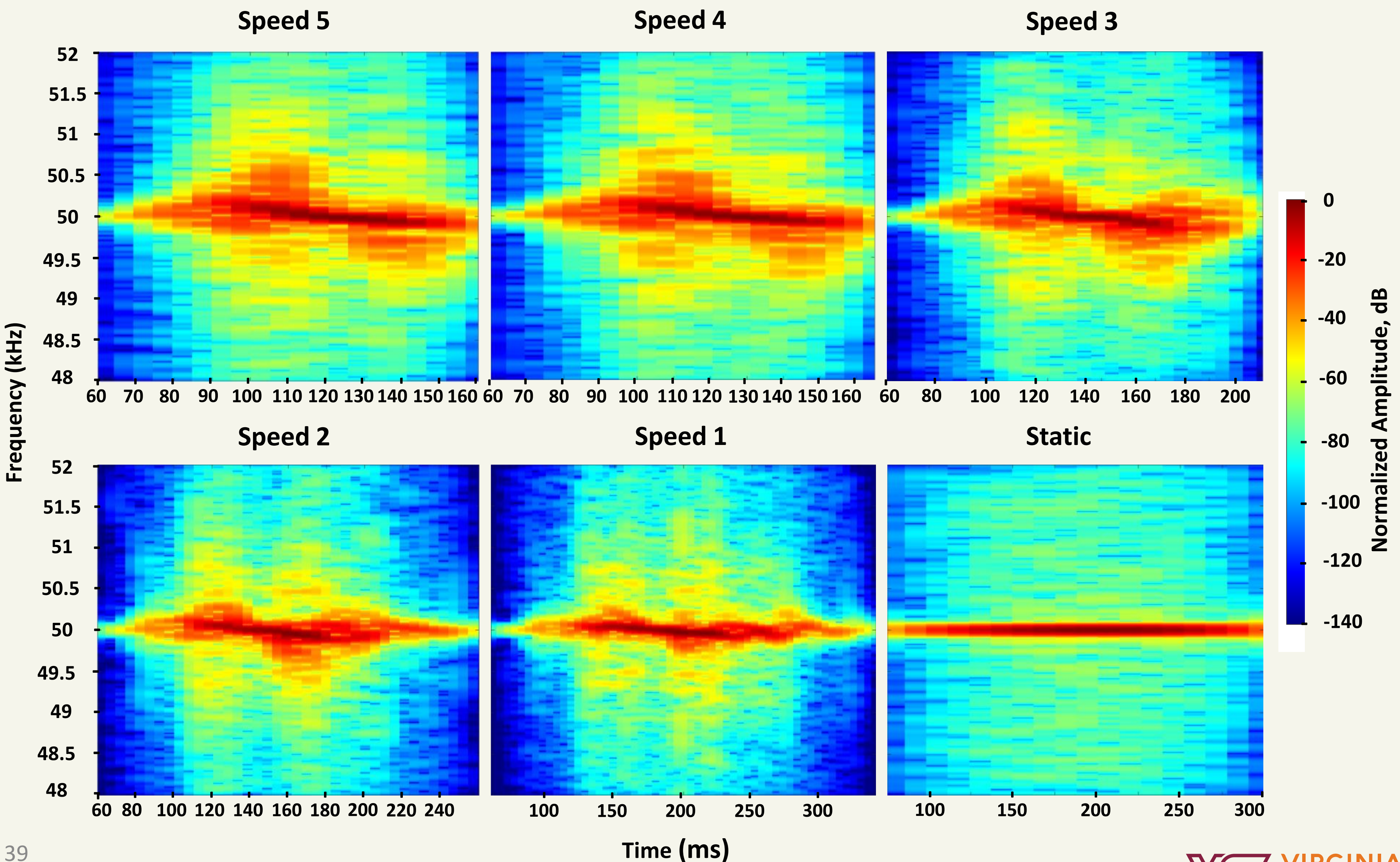
$$d_{50kHz} = \frac{2 * (0.05m)^2}{(\frac{c}{50\ kHz})} = \sim 0.73\ m$$

Doppler Motion Characterization: Downwards Defrm.



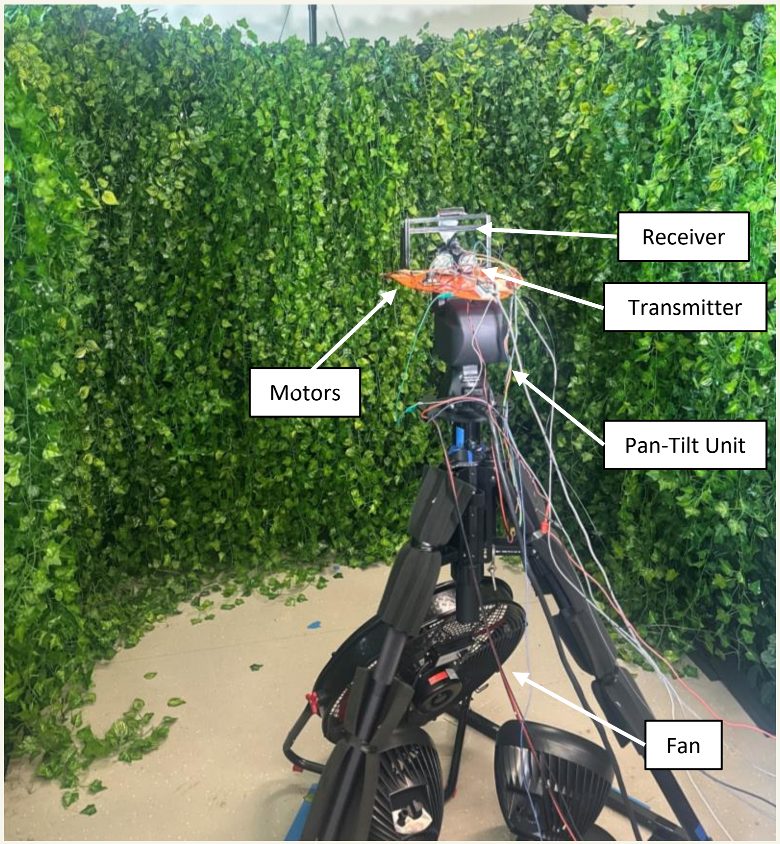
VIRGINIA TECH.

Doppler Motion Characterization: Sideways Defrm.

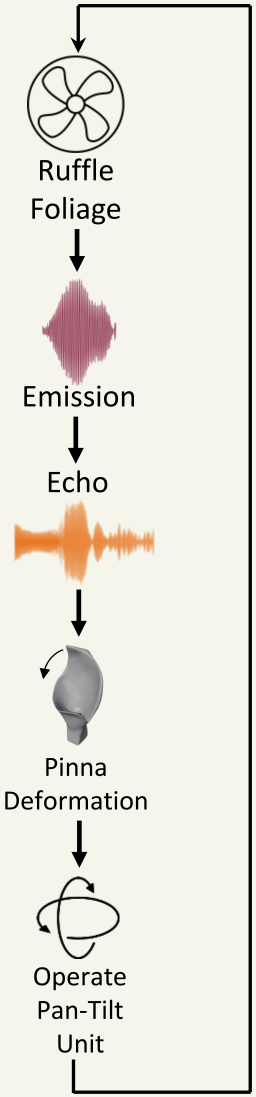


Updated Laboratory Setup & Control Scheme

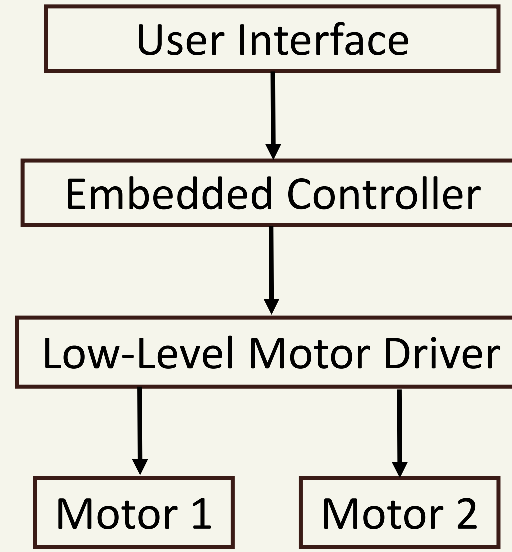
Physical Setup



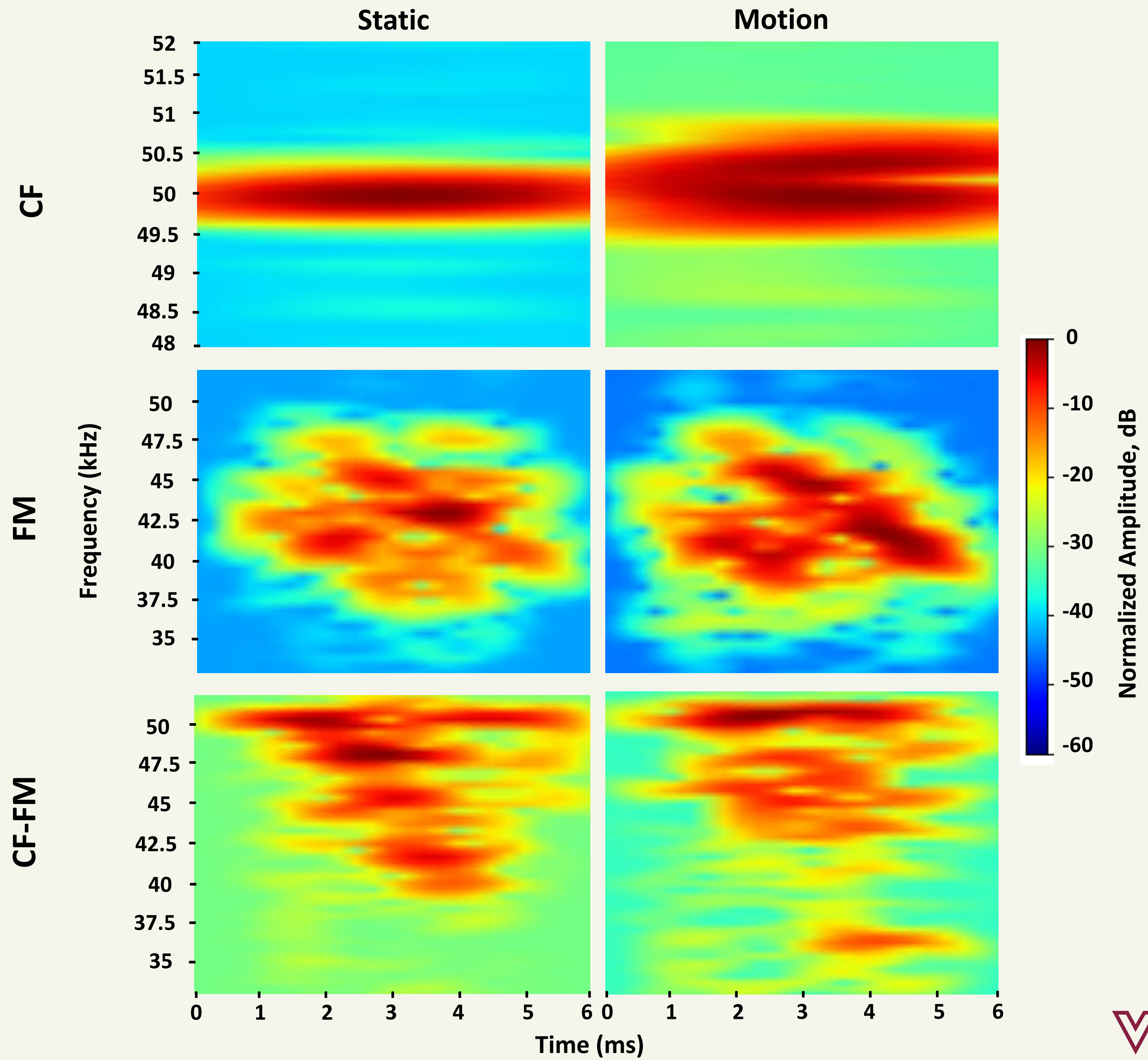
Control Scheme for the Experiments



System Control Hierarchy

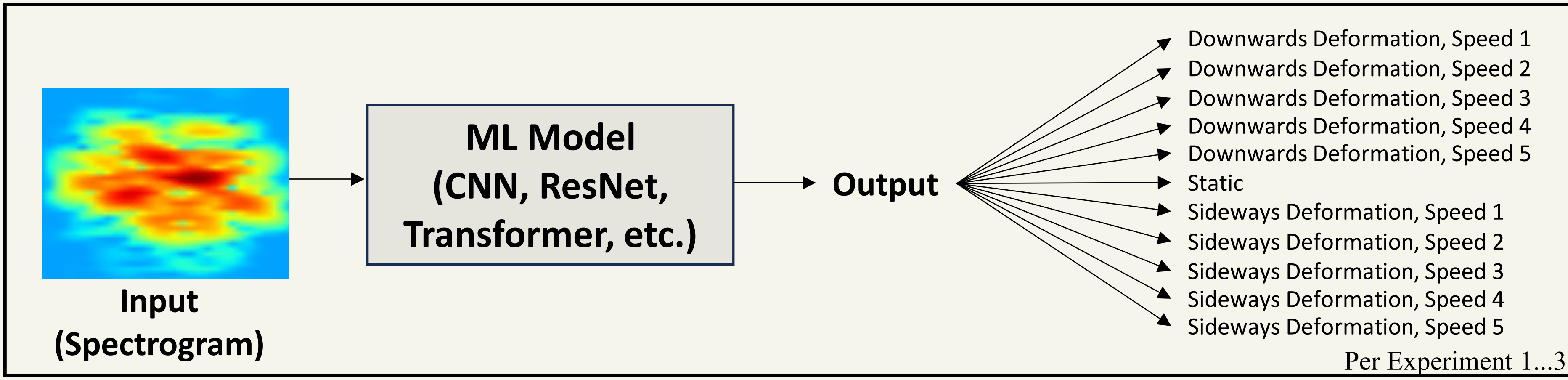


Clutter Echo Doppler Examples



VIRGINIA TECH

Data & Evaluation Methods

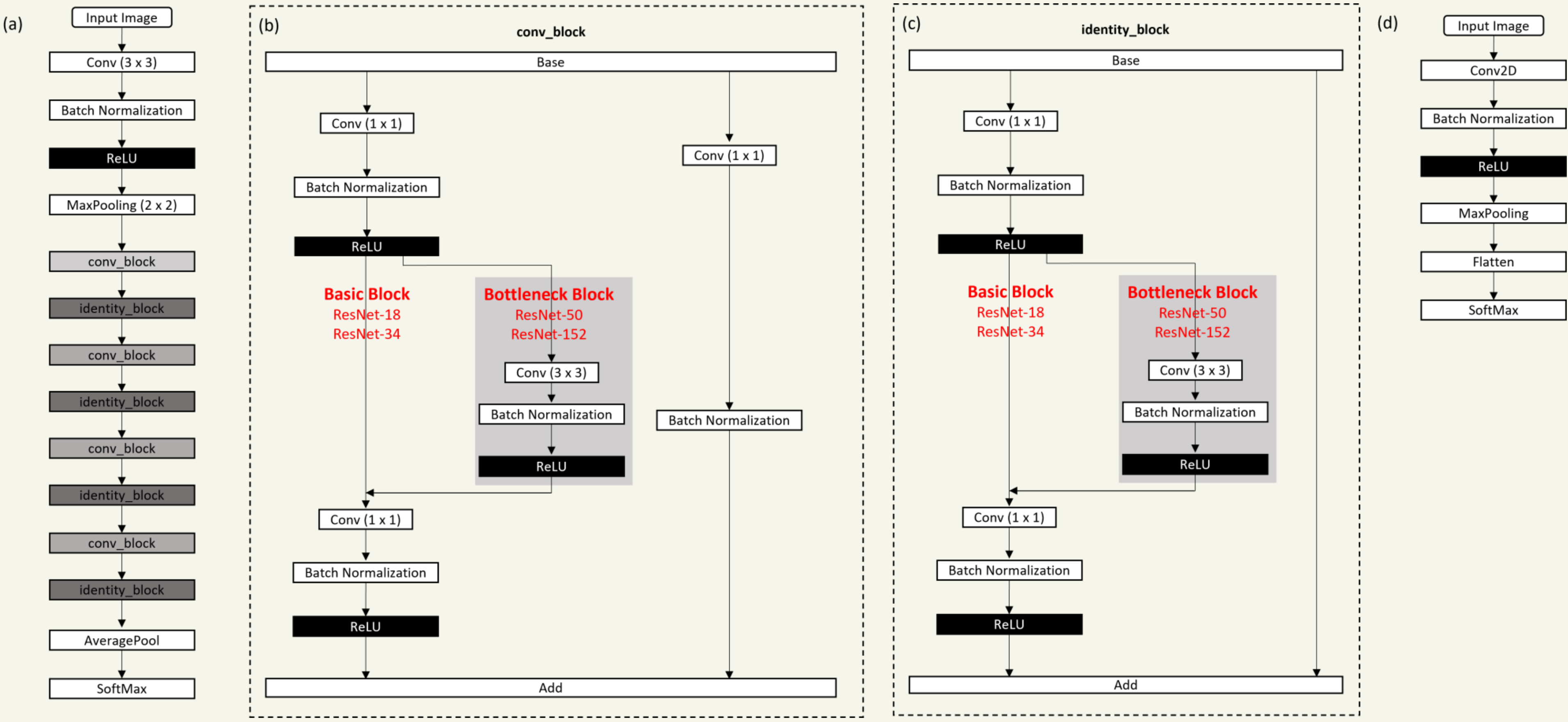


Data
1,000 samples per class
11 classes per transmit signal
3 transmitted signals (CF, FM, CF-FM)

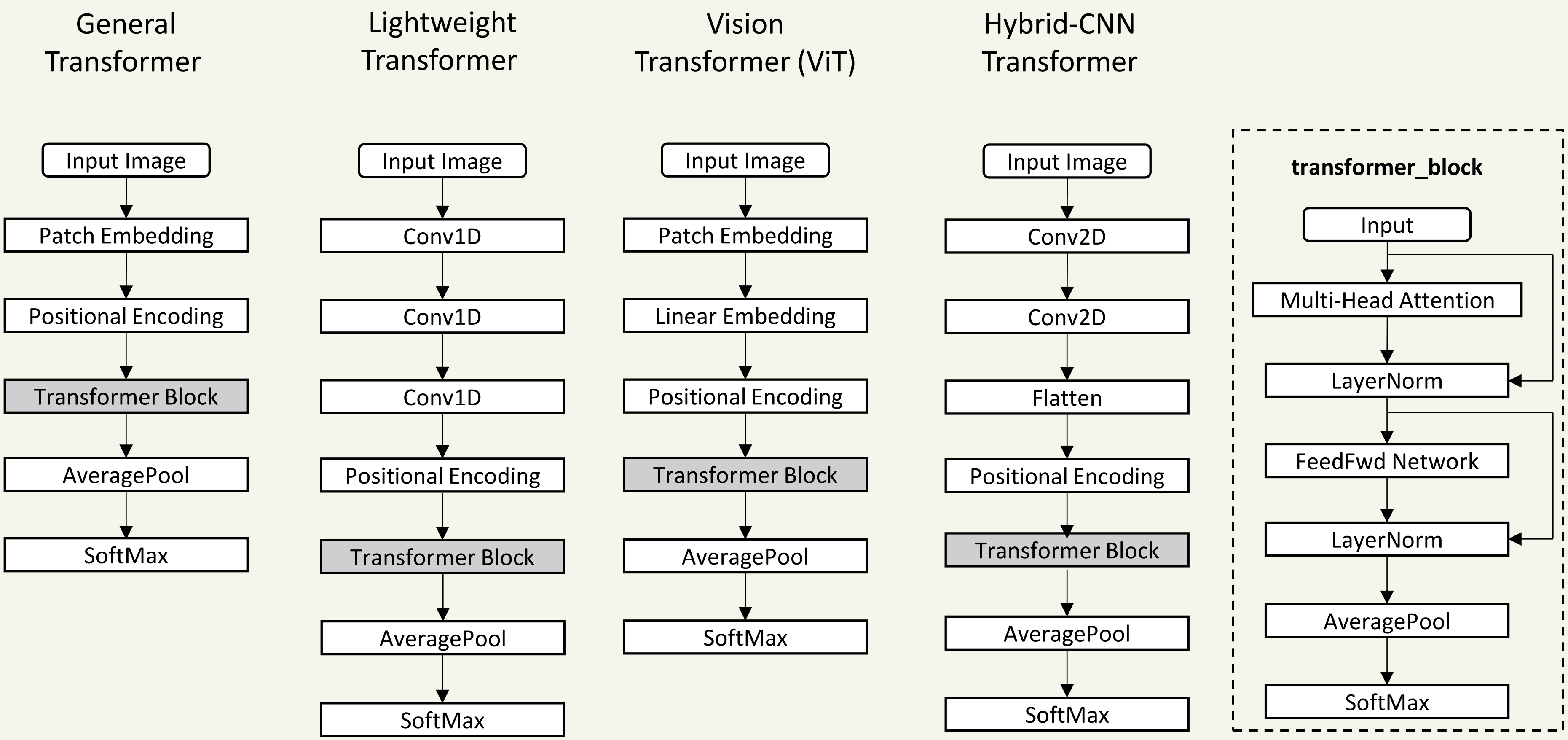
Experiments
Experiment 1: Transmitted Signal – CF
Experiment 2: Transmitted Signal – FM
Experiment 3: Transmitted Signal – CF-FM

- **11,000** data samples over 11 classes per Transmit Signal
- ***k-Folds*** Cross Validation ($k = 5$)
- **80%** training / **20%** testing per fold
- Averaged Across Folds Reported
- Early stopping + checkpointing → best model per fold

ResNet Architectures



Transformer-Based Network Architectures

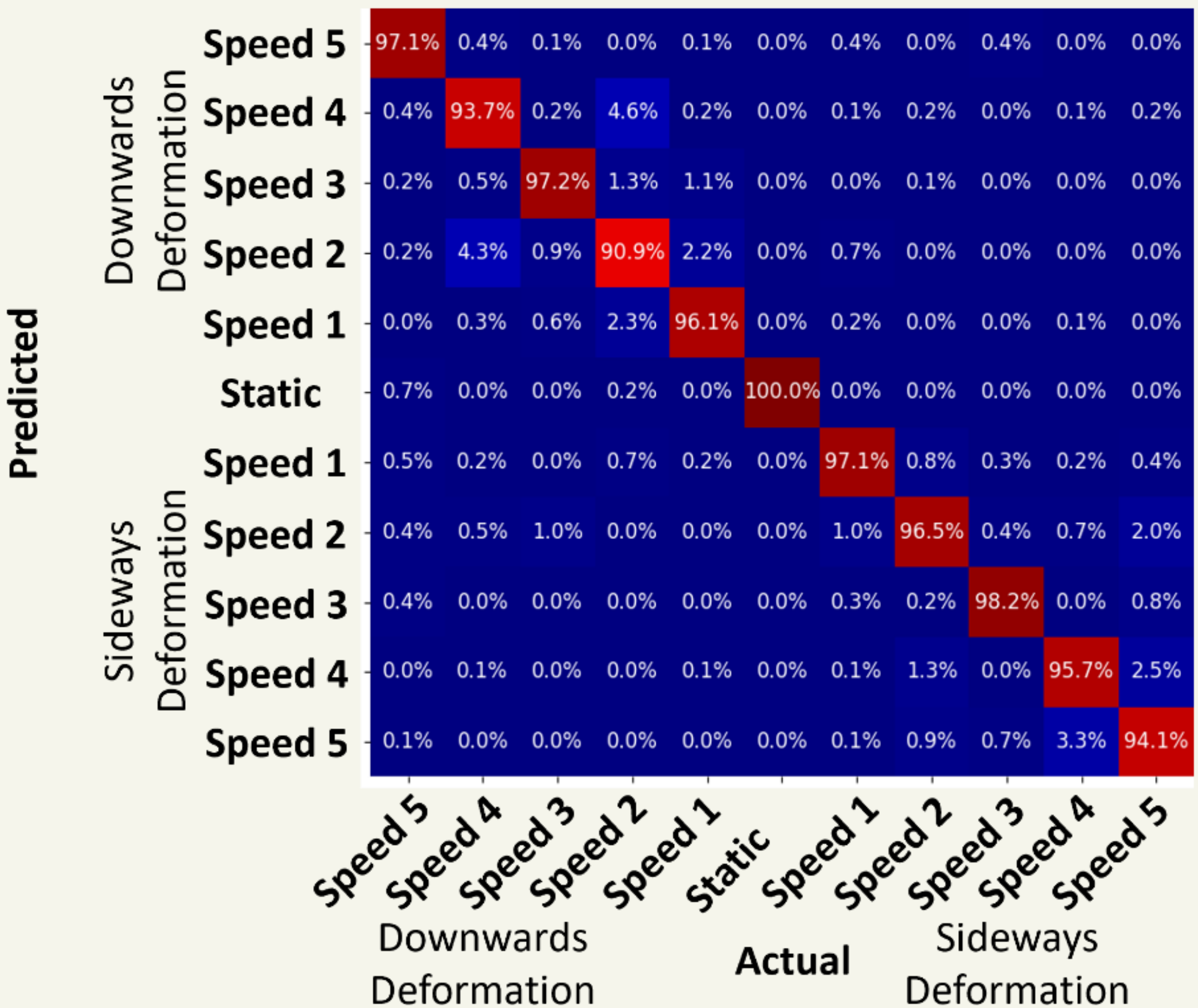


Confusion Matrix of Best-Performing Model on CF

Predicted \ Actual	Downwards Deformation Speed 5	Downwards Deformation Speed 4	Downwards Deformation Speed 3	Downwards Deformation Speed 2	Downwards Deformation Speed 1	Static	Sideways Deformation Speed 1	Sideways Deformation Speed 2	Sideways Deformation Speed 3	Sideways Deformation Speed 4	Sideways Deformation Speed 5
Downwards Deformation Speed 5	64.7%	13.9%	1.5%	0.2%	0.7%	0.0%	0.4%	1.6%	1.6%	8.4%	13.1%
Downwards Deformation Speed 4	7.9%	37.0%	7.0%	3.0%	2.2%	0.0%	1.3%	8.7%	6.7%	5.7%	10.8%
Downwards Deformation Speed 3	0.9%	4.4%	28.7%	11.6%	6.7%	0.3%	1.0%	12.0%	10.6%	4.1%	4.0%
Downwards Deformation Speed 2	0.5%	4.2%	13.0%	32.3%	17.5%	0.4%	15.0%	7.7%	4.8%	0.4%	0.8%
Downwards Deformation Speed 1	0.9%	4.2%	15.0%	23.8%	51.0%	0.5%	17.6%	11.7%	9.3%	1.7%	2.2%
Static	0.4%	0.0%	0.0%	2.2%	0.7%	93.7%	9.1%	0.4%	1.3%	0.0%	0.0%
Sideways Deformation Speed 1	0.5%	3.1%	4.3%	16.6%	10.8%	4.5%	46.1%	8.4%	8.4%	0.4%	1.1%
Sideways Deformation Speed 2	0.8%	5.6%	10.2%	3.9%	5.5%	0.0%	3.8%	23.5%	12.5%	5.2%	6.1%
Sideways Deformation Speed 3	1.5%	6.3%	9.9%	5.5%	3.1%	0.5%	4.9%	12.7%	26.4%	4.2%	7.5%
Sideways Deformation Speed 4	7.6%	10.0%	4.4%	0.6%	1.1%	0.0%	0.1%	4.5%	8.5%	51.0%	18.1%
Sideways Deformation Speed 5	14.3%	11.4%	6.1%	0.2%	0.7%	0.1%	0.6%	8.7%	10.0%	18.9%	36.3%

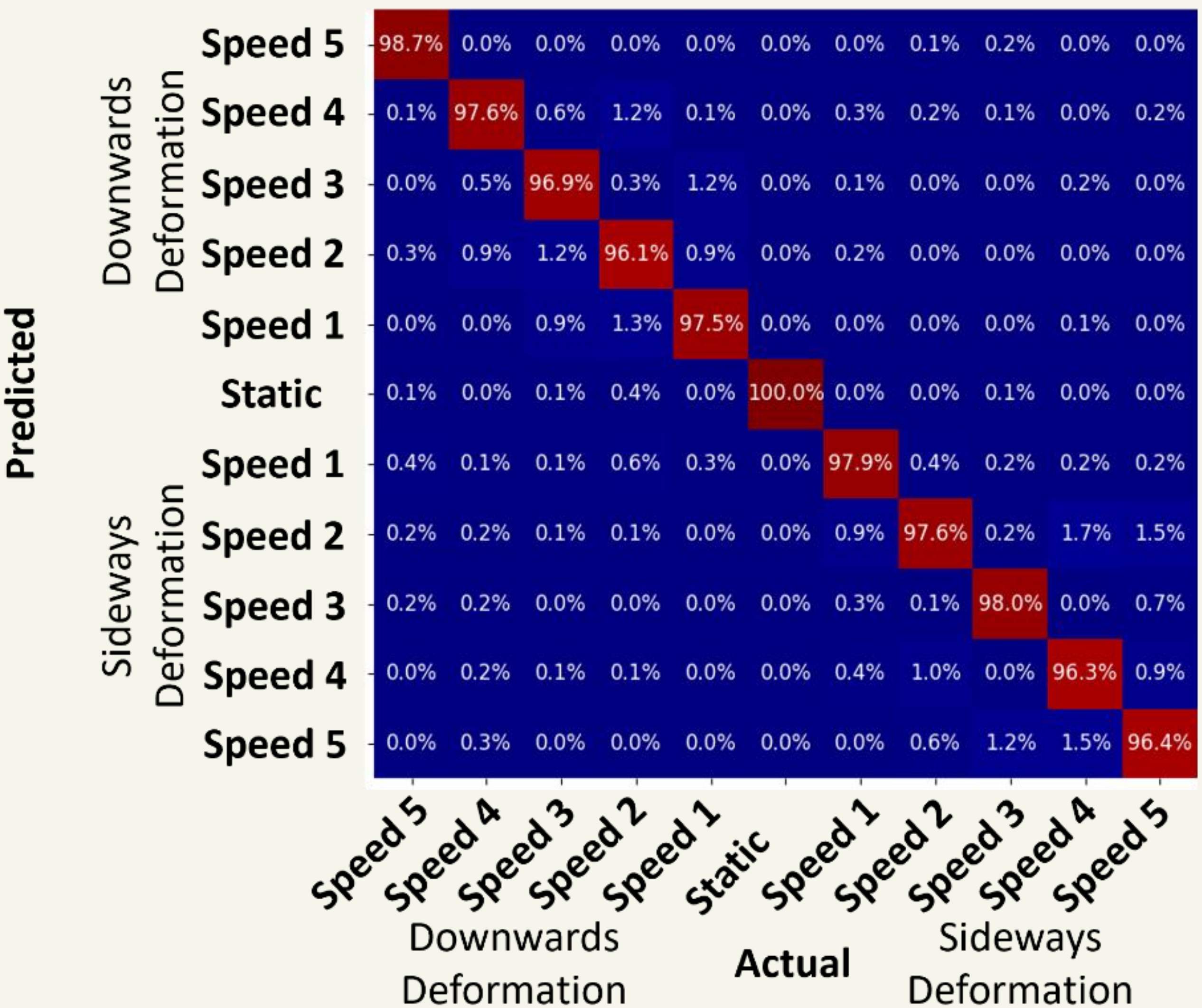
ResNet-18
Average Classification
Accuracy: 48.31%

Confusion Matrix of Best-Performing Model on FM



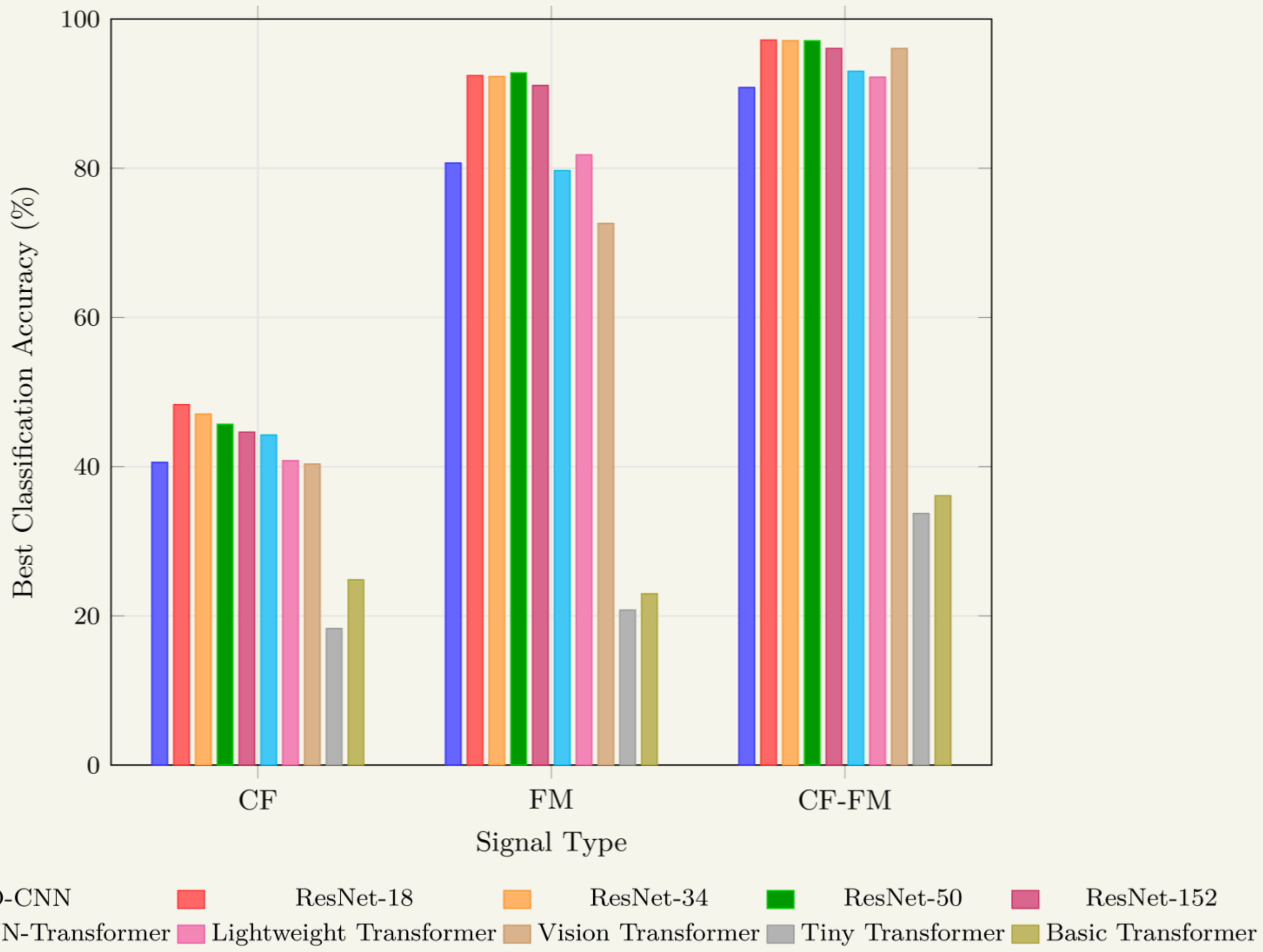
ResNet-50
Average Classification
Accuracy: 92.78%

Confusion Matrix of Best-Performing Model on CF-FM

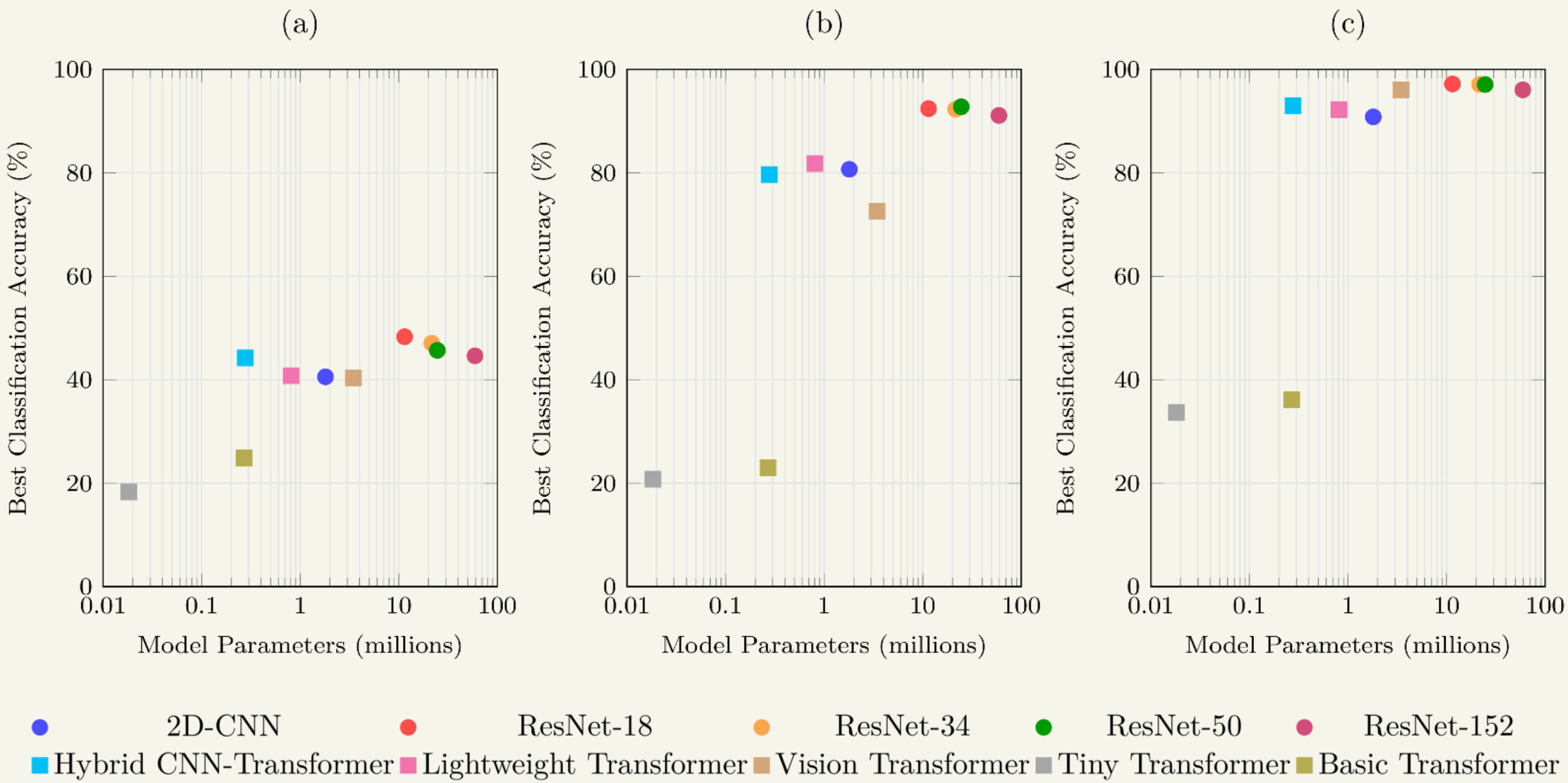


ResNet-18
Average Classification
Accuracy: 97.19%

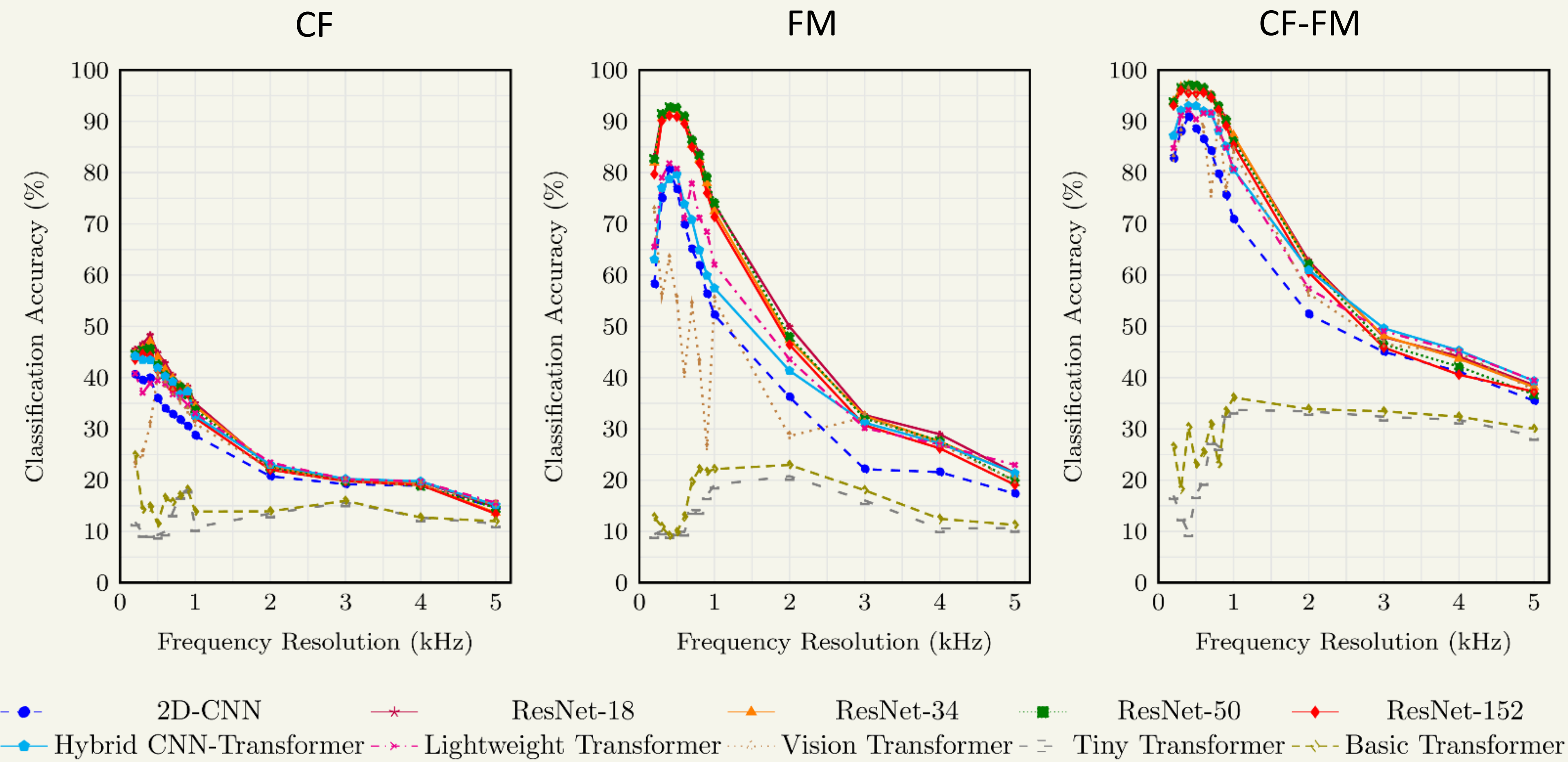
Best Classification Accuracy per Signal Type & Network



Best Classification Accuracy vs Model Parameter Count



Time-Frequency Resolution Tradeoff



UMAP Clustering Analysis

Unsupervised UMAP Clustering on Raw Data

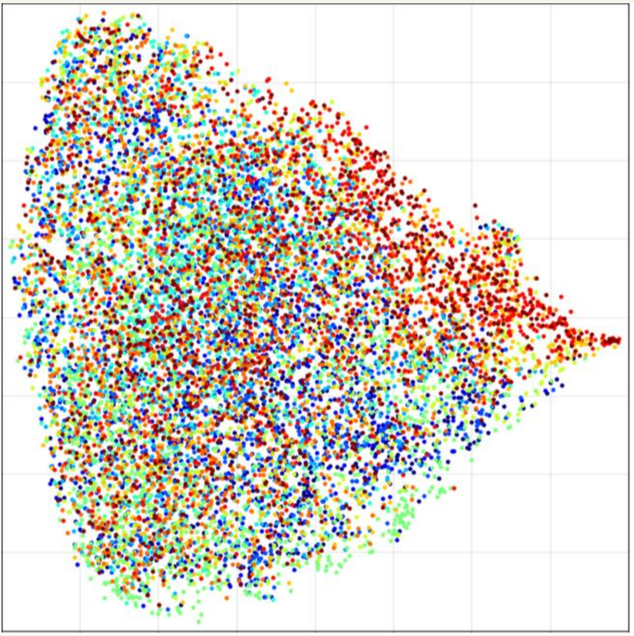
Input	Labeled
Raw Data	No

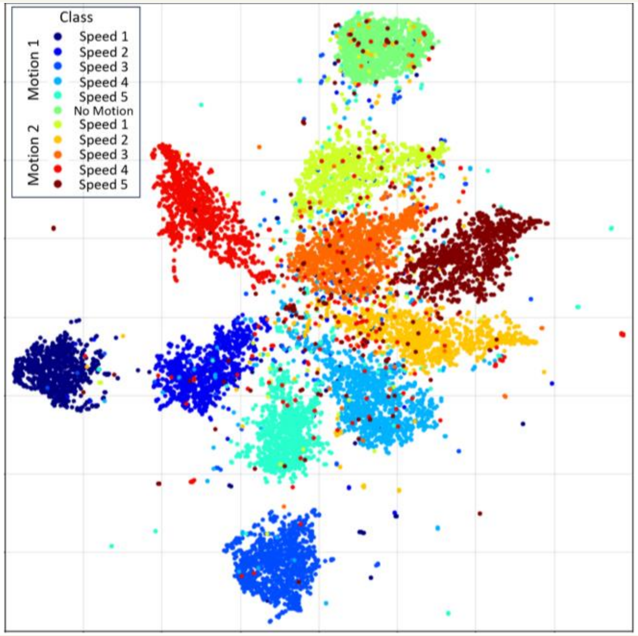
Supervised UMAP Clustering on Raw Data

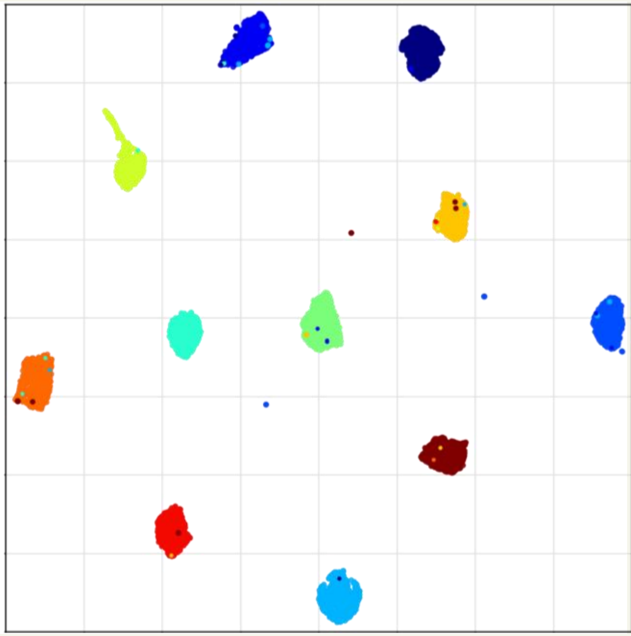
Input	Labeled
Raw Data	Yes

Unsupervised UMAP Clustering on Final Layer

Input	Labeled
Learned Features	No







Agenda

- Motivation & Prior Art
- My Contributions
  - Static Pinna Shape Conformations on Clutter Echoes
    - Methods
    - Results & Discussion
  - Dynamic Pinna Motions on Clutter Echoes
    - Modified Methods
    - Results & Discussion
- Summary & Conclusion

Summary & Conclusion

- Both **static shape variation** and **dynamic deformation** influence clutter echoes
- **Dynamic motions** produce consistent, discriminable signatures across different shapes and speeds.
- FM and CF-FM signals carry richer motion information than narrowband CF signals.
- Machine Learning reliably distinguished motion type and speed → consistent acoustic coding.
- The consistency in the information extracted despite the variability in the environment may be essential for understanding the potential sensory benefits of pinna dynamics in complex biosonar tasks.
- **Future Work:** Test dynamic deformations on downstream sensory tasks in clutter
    - Extending This Work To a Sensory Task (e.g. Target Detection)
        - Establish baseline static performance
        - Compare against dynamic performance

Backup Slides

Applications in the Field

Motivation Outline

Overall Flow

1. Performance gap exists between engineered sonar and bat biosonar (Slide 10)
   1. **Engineered Sonar** minimizes beamwidth (i.e. narrow, high-gain beams)
   2. **Biosonar** exhibits broader, variable beams despite having the physical capacity to narrow them
      1. Implies that bats prioritize adaptive information richness over geometric efficiency

2. What do bats do that engineered sonar does not? What could explain this? (Slide 10)
   1. Clearly deviate from the elliptical-transduce limit which motivates further investigation into this phenomena
   2. The elliptical transducer model does not apply to bats → okay let's see the mechanism.

3. Bats Have Two Distinct Types of Pinna Motions: Rigid and Non-Rigid Deformation (Slide 11)

4. Non-Rigid Deformations demonstrated that dynamic shape changes in pinna can add independent sensory information and improve directional resolution (Slide 12)

5. This work addresses this gap through controlled experiments on static and dynamically deforming pinna in clutter, providing the first quantitative evidence linking ear dynamics to clutter-echo sensing performance. (Slide 13)

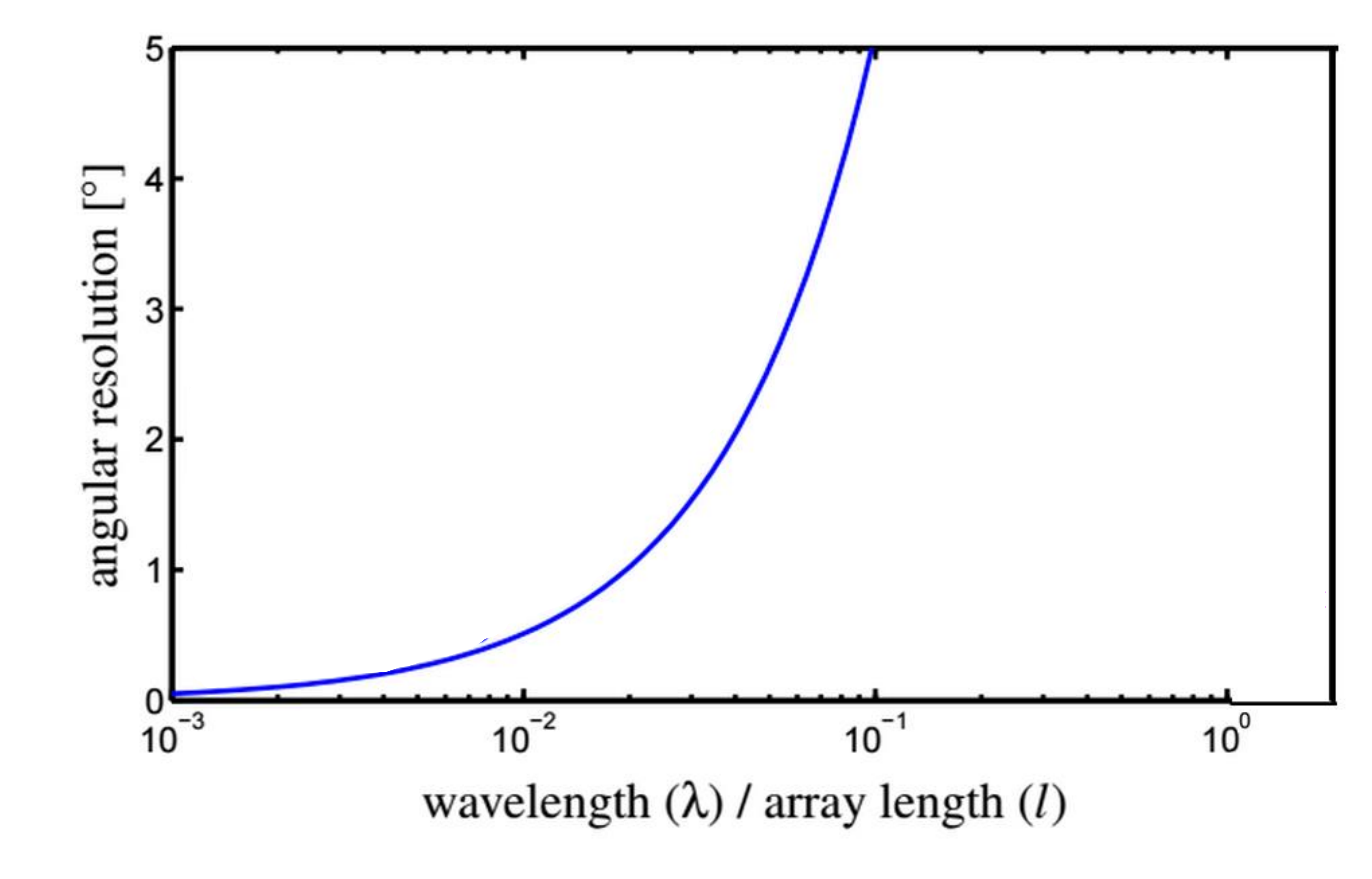
Principals of Sonar

Detection

Localization

Identification

Man-Made Sonar and Limitations in Performance



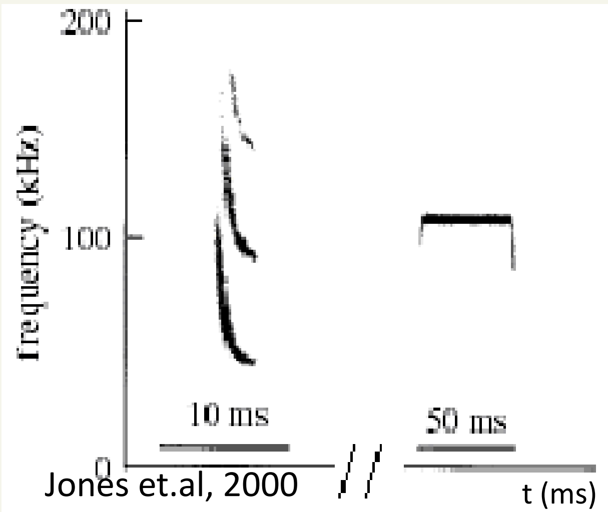
Geberl, C., Kugler, K., & Wiegrebe, L. (2019). The spatial resolution of bat biosonar quantified with a visual-resolution paradigm. *Current Biology, 29*(11), 1842–1846.

Simmons, J. A. (1971). Echolocation in bats: Signal processing of echoes for target range. *Science, 171*(3974), 925–928.

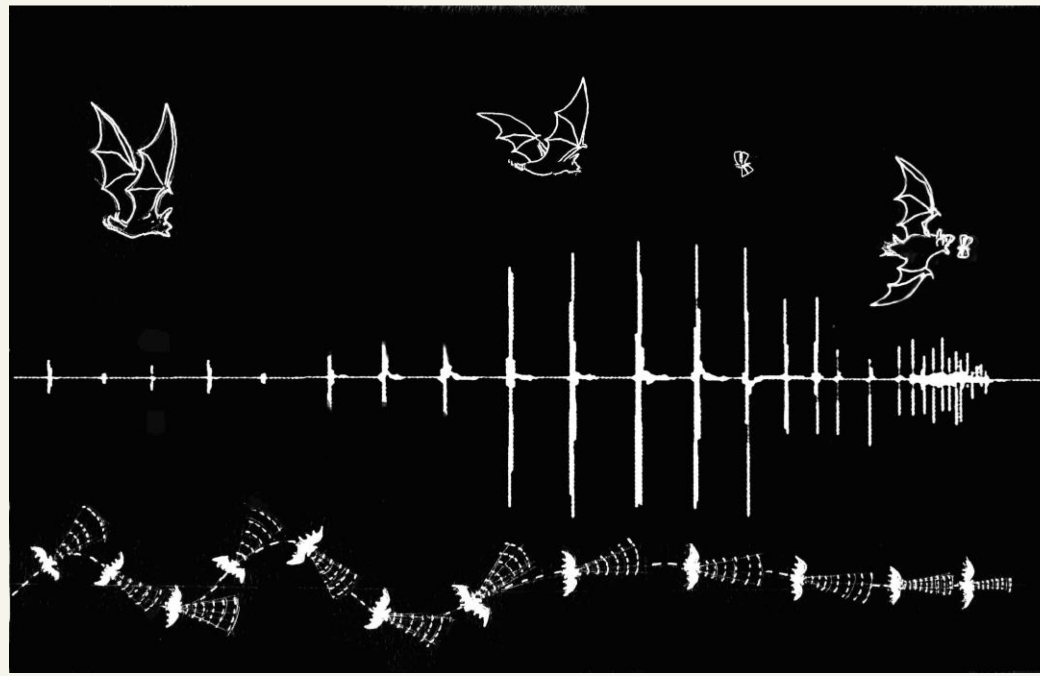
Sutlive, J. V. (2020). *Biomimetic sonar design and the investigation of the role of peripheral dynamics for target classification in bat biosonar*

Navigation in Cluttered Environments

FM bat CF-FM bat



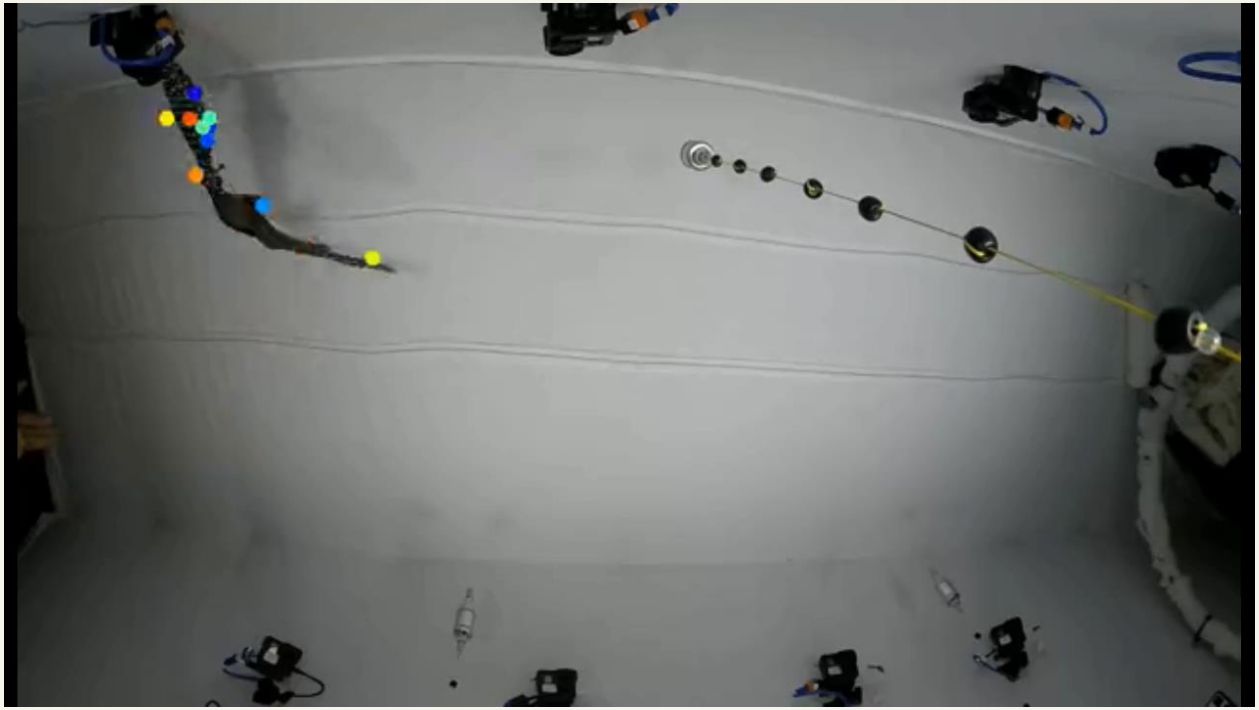
Jones et.al, 2000



VIRGINIA TECH

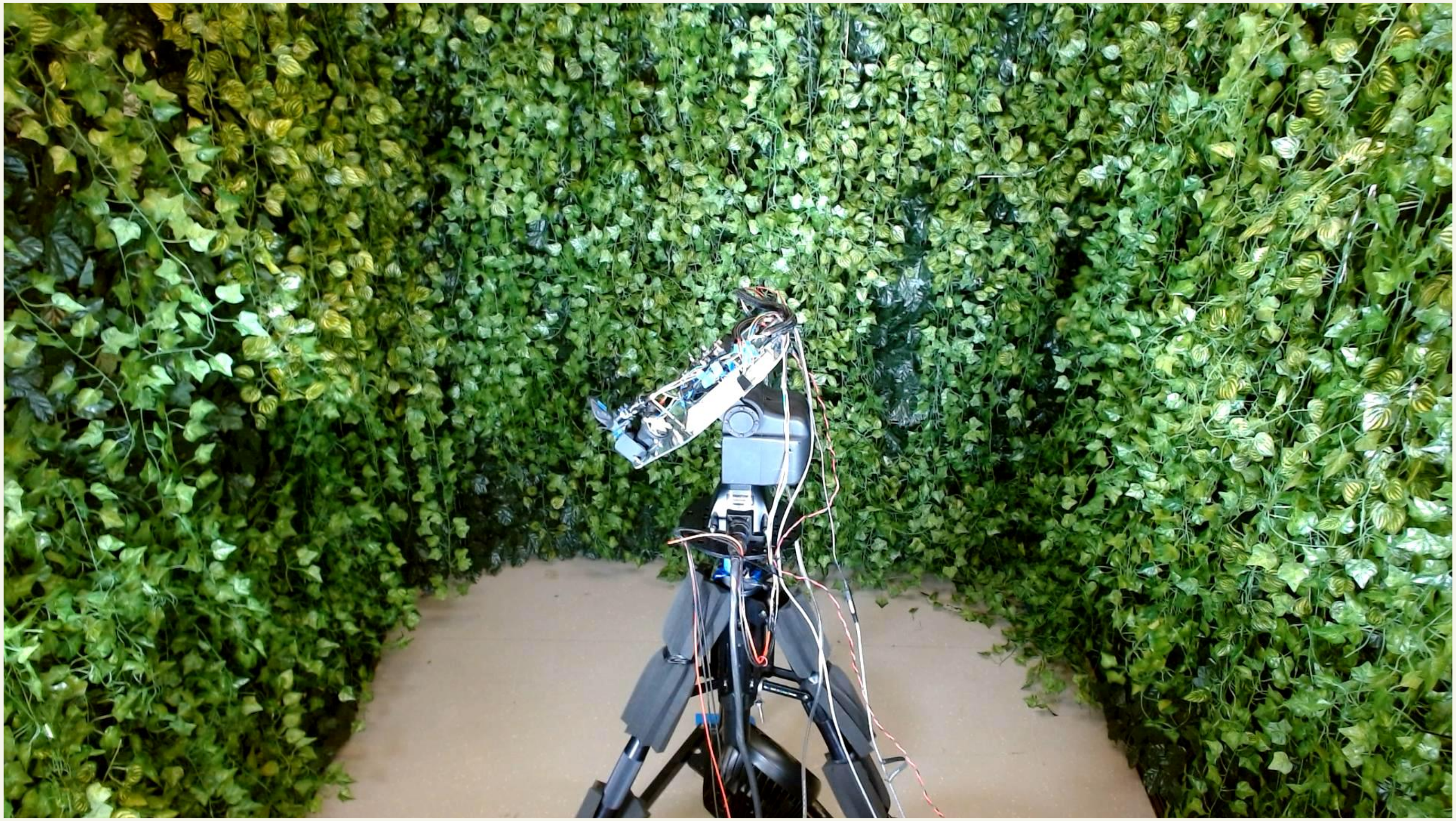
Overview: What can we learn from bats?

1. Bats are able to navigate in complex environments with miniature sonar systems
   1. Adaptable performance that can surpass that of engineered sonar
2. These miniature sonar systems have dynamic peripheries and two distinct types of motions
   1. Rigid Motions
   2. Non-Rigid Motions
3. These distinct motions encode useful information that may aid in certain sensing and navigation tasks

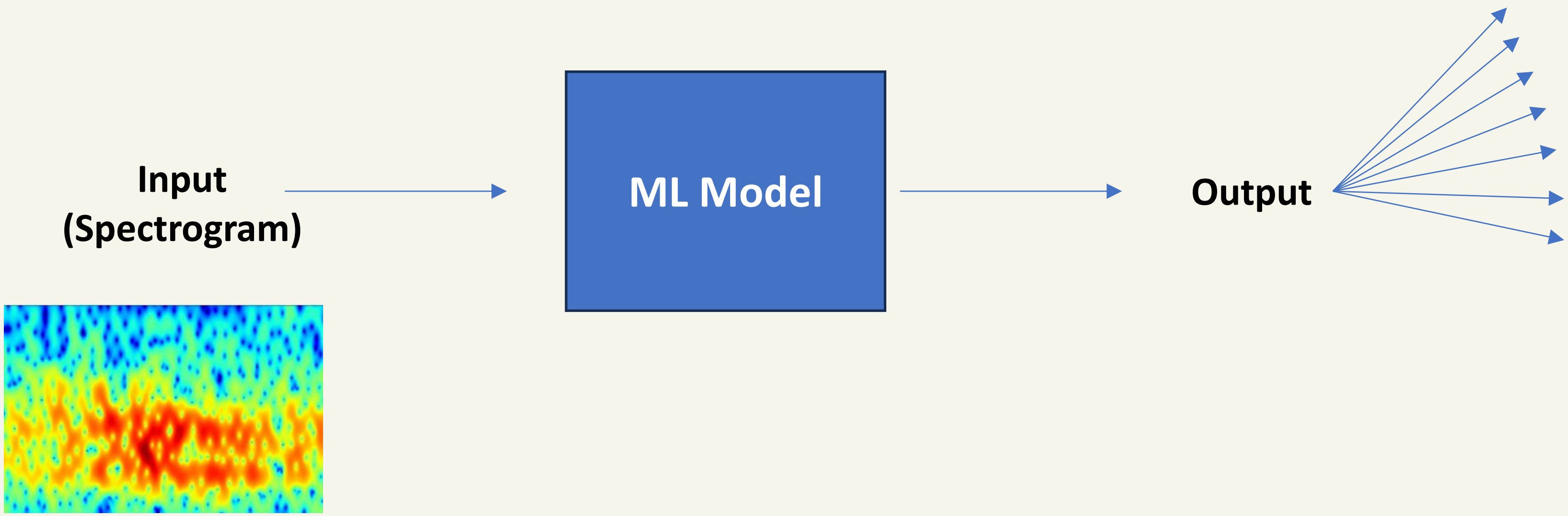


Deforming Ears in Horseshoe Bats

Example of an Experiment

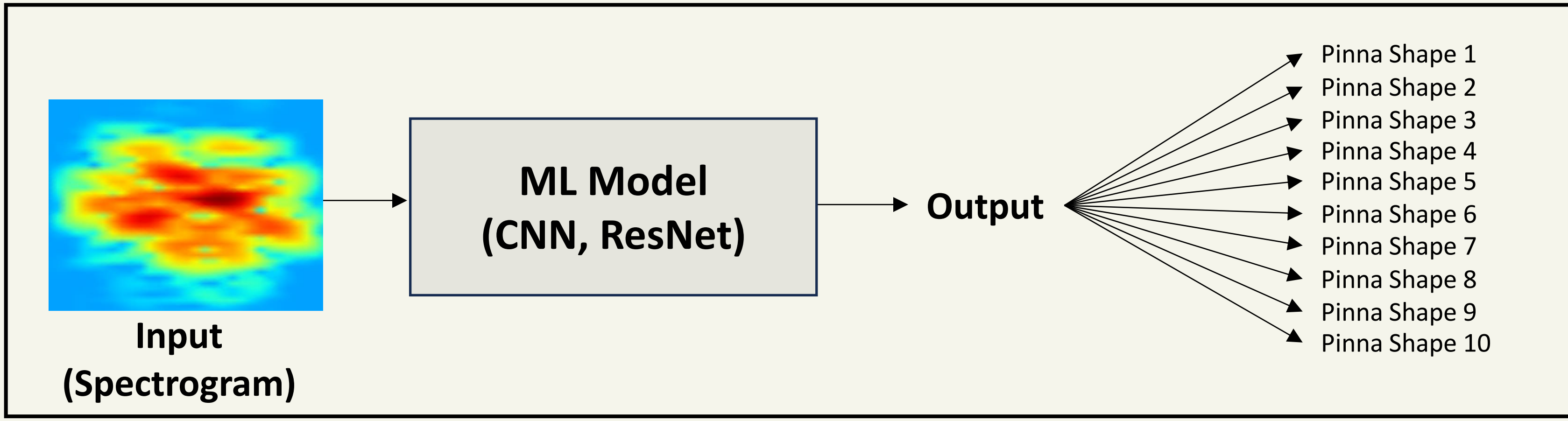


Machine Learning Approach



- ~1,500 samples/class
- Train-Test-Validation Split:
  - 60%-20%-20%
  - 900-300-300
- Test is unseen to network

Data & Evaluation Methods



Data
1,500 samples per class
10 classes

- **15,000** data samples over 10 classes per Transmit Signal
- ***k-Folds*** Cross Validation ($k = 5$)
- **80%** training / **20%** testing per fold
- Averaged Across Folds Reported
- Early stopping + checkpointing → best model per fold

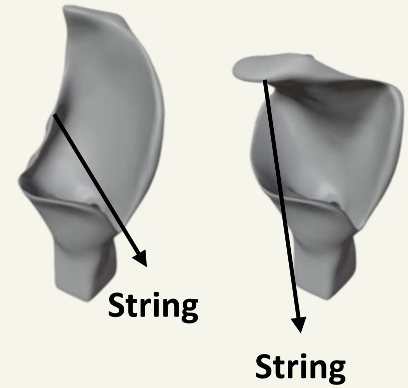
Designing an Experiment

Agitate Foliage with Previous Method

Classifications & Analysis To Be Made:

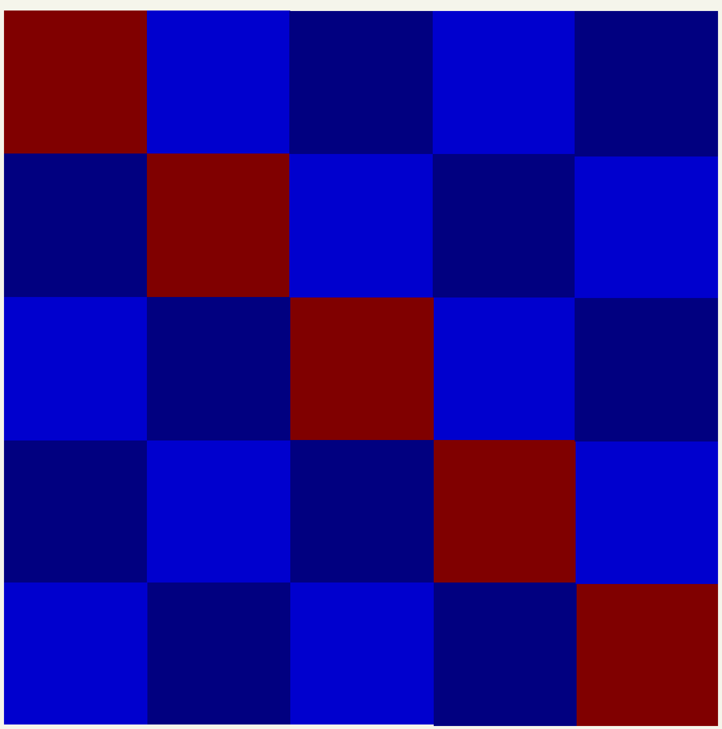
- Shape 1: CF vs CF at 20% Speed Deformation
- Shape 1: CF vs CF at 40% Speed Deformation
- Shape 1: CF vs CF at 60% Speed Deformation
- Shape 1: CF vs CF at 80% Speed Deformation
- Shape 1: CF vs CF at 100% Speed Deformation

Shape 1 (10, 0, 0) **Shape 2** (0, 10, 0)



Actual

X% Deformation Speed for A Given Tx Signal



X% Deformation Speed for A Given Tx Signal

Predicted

Analysis: Spectrograms, Classifier Accuracy, Confusion Matrices, Time-Frequency Analysis, UMAP Embeddings

Predicted \ Actual	Downwards Deformation Speed 5	Downwards Deformation Speed 4	Downwards Deformation Speed 3	Downwards Deformation Speed 2	Downwards Deformation Speed 1	Static	Sideways Deformation Speed 1	Sideways Deformation Speed 2	Sideways Deformation Speed 3	Sideways Deformation Speed 4	Sideways Deformation Speed 5
Downwards Deformation Speed 5	64.7%	13.9%	1.5%	0.2%	0.7%	0.0%	0.4%	1.6%	1.6%	8.4%	13.1%
Downwards Deformation Speed 4	7.9%	37.0%	7.0%	3.0%	2.2%	0.0%	1.3%	8.7%	6.7%	5.7%	10.8%
Downwards Deformation Speed 3	0.9%	4.4%	28.7%	11.6%	6.7%	0.3%	1.0%	12.0%	10.6%	4.1%	4.0%
Downwards Deformation Speed 2	0.5%	4.2%	13.0%	32.3%	17.5%	0.4%	15.0%	7.7%	4.8%	0.4%	0.8%
Downwards Deformation Speed 1	0.9%	4.2%	15.0%	23.8%	51.0%	0.5%	17.6%	11.7%	9.3%	1.7%	2.2%
Static	0.4%	0.0%	0.0%	2.2%	0.7%	93.7%	9.1%	0.4%	1.3%	0.0%	0.0%
Sideways Deformation Speed 1	0.5%	3.1%	4.3%	16.6%	10.8%	4.5%	46.1%	8.4%	8.4%	0.4%	1.1%
Sideways Deformation Speed 2	0.8%	5.6%	10.2%	3.9%	5.5%	0.0%	3.8%	23.5%	12.5%	5.2%	6.1%
Sideways Deformation Speed 3	1.5%	6.3%	9.9%	5.5%	3.1%	0.5%	4.9%	12.7%	26.4%	4.2%	7.5%
Sideways Deformation Speed 4	7.6%	10.0%	4.4%	0.6%	1.1%	0.0%	0.1%	4.5%	8.5%	51.0%	18.1%
Sideways Deformation Speed 5	14.3%	11.4%	6.1%	0.2%	0.7%	0.1%	0.6%	8.7%	10.0%	18.9%	36.3%

Predicted \ Actual	Downwards Deformation Speed 5	Downwards Deformation Speed 4	Downwards Deformation Speed 3	Downwards Deformation Speed 2	Downwards Deformation Speed 1	Static	Sideways Deformation Speed 1	Sideways Deformation Speed 2	Sideways Deformation Speed 3	Sideways Deformation Speed 4	Sideways Deformation Speed 5
Downwards Deformation Speed 5	97.1%	0.4%	0.1%	0.0%	0.1%	0.0%	0.4%	0.0%	0.4%	0.0%	0.0%
Downwards Deformation Speed 4	0.4%	93.7%	0.2%	4.6%	0.2%	0.0%	0.1%	0.2%	0.0%	0.1%	0.2%
Downwards Deformation Speed 3	0.2%	0.5%	97.2%	1.3%	1.1%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%
Downwards Deformation Speed 2	0.2%	4.3%	0.9%	90.9%	2.2%	0.0%	0.7%	0.0%	0.0%	0.0%	0.0%
Downwards Deformation Speed 1	0.0%	0.3%	0.6%	2.3%	96.1%	0.0%	0.2%	0.0%	0.0%	0.1%	0.0%
Static	0.7%	0.0%	0.0%	0.2%	0.0%	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Sideways Deformation Speed 1	0.5%	0.2%	0.0%	0.7%	0.2%	0.0%	97.1%	0.8%	0.3%	0.2%	0.4%
Sideways Deformation Speed 2	0.4%	0.5%	1.0%	0.0%	0.0%	0.0%	1.0%	96.5%	0.4%	0.7%	2.0%
Sideways Deformation Speed 3	0.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.3%	0.2%	98.2%	0.0%	0.8%
Sideways Deformation Speed 4	0.0%	0.1%	0.0%	0.0%	0.1%	0.0%	0.1%	1.3%	0.0%	95.7%	2.5%
Sideways Deformation Speed 5	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.9%	0.7%	3.3%	94.1%

Predicted \ Actual	Downwards Deformation Speed 5	Downwards Deformation Speed 4	Downwards Deformation Speed 3	Downwards Deformation Speed 2	Downwards Deformation Speed 1	Static	Sideways Deformation Speed 1	Sideways Deformation Speed 2	Sideways Deformation Speed 3	Sideways Deformation Speed 4	Sideways Deformation Speed 5
Downwards Deformation Speed 5	98.7%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.2%	0.0%	0.0%
Downwards Deformation Speed 4	0.1%	97.6%	0.6%	1.2%	0.1%	0.0%	0.3%	0.2%	0.1%	0.0%	0.2%
Downwards Deformation Speed 3	0.0%	0.5%	96.9%	0.3%	1.2%	0.0%	0.1%	0.0%	0.0%	0.2%	0.0%
Downwards Deformation Speed 2	0.3%	0.9%	1.2%	96.1%	0.9%	0.0%	0.2%	0.0%	0.0%	0.0%	0.0%
Downwards Deformation Speed 1	0.0%	0.0%	0.9%	1.3%	97.5%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%
Static	0.1%	0.0%	0.1%	0.4%	0.0%	100.0%	0.0%	0.0%	0.1%	0.0%	0.0%
Sideways Deformation Speed 1	0.4%	0.1%	0.1%	0.6%	0.3%	0.0%	97.9%	0.4%	0.2%	0.2%	0.2%
Sideways Deformation Speed 2	0.2%	0.2%	0.1%	0.1%	0.0%	0.0%	0.9%	97.6%	0.2%	1.7%	1.5%
Sideways Deformation Speed 3	0.2%	0.2%	0.0%	0.0%	0.0%	0.0%	0.3%	0.1%	98.0%	0.0%	0.7%
Sideways Deformation Speed 4	0.0%	0.2%	0.1%	0.1%	0.0%	0.0%	0.4%	1.0%	0.0%	96.3%	0.9%
Sideways Deformation Speed 5	0.0%	0.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.6%	1.2%	1.5%	96.4%

What We Discussed & Timeline Constraints

- Idea 1: Deterministic Target In Clutter
  - Novel
  - Detection – Possible? Not Possible?
  - Shapes – Help? Don't Help?
  - Possibly Explore: Doppler
- Idea 2: Doppler Classification
  - New, Requires Additional Hardware, Setup, & Debugging
  - Can Explore

Timeline & Funding Constraints

- Preliminary Exam: Spring 2025
- Paper I Review Comments: Summer 2025
- Paper II Submission: Summer 2025
- Paper II Review Comments: September/October 2025
- **Start of Semester Defense Exception: September/October 2025**

Can we detect the presence or absence of a deterministic target embedded in clutter?

Previous: Shown that clutter has a consistent effect. Now, we want to explore if within this we can perform meaningful tasks as a bat does.

Biological Relevance: In bats, this relates to navigation, obstacle avoidance, prey tracking.

Context: This equation governs echo power return from an acoustic target:

$$P_r = P_t \frac{\sigma}{(4\pi r^2)^2} e^{-2\alpha(f)r} = Received\ Power\ Equation$$

Deterministic Target: A compact, acoustically reflective object with known, fixed geometry and material properties. Produces predictable echoes under identical conditions.

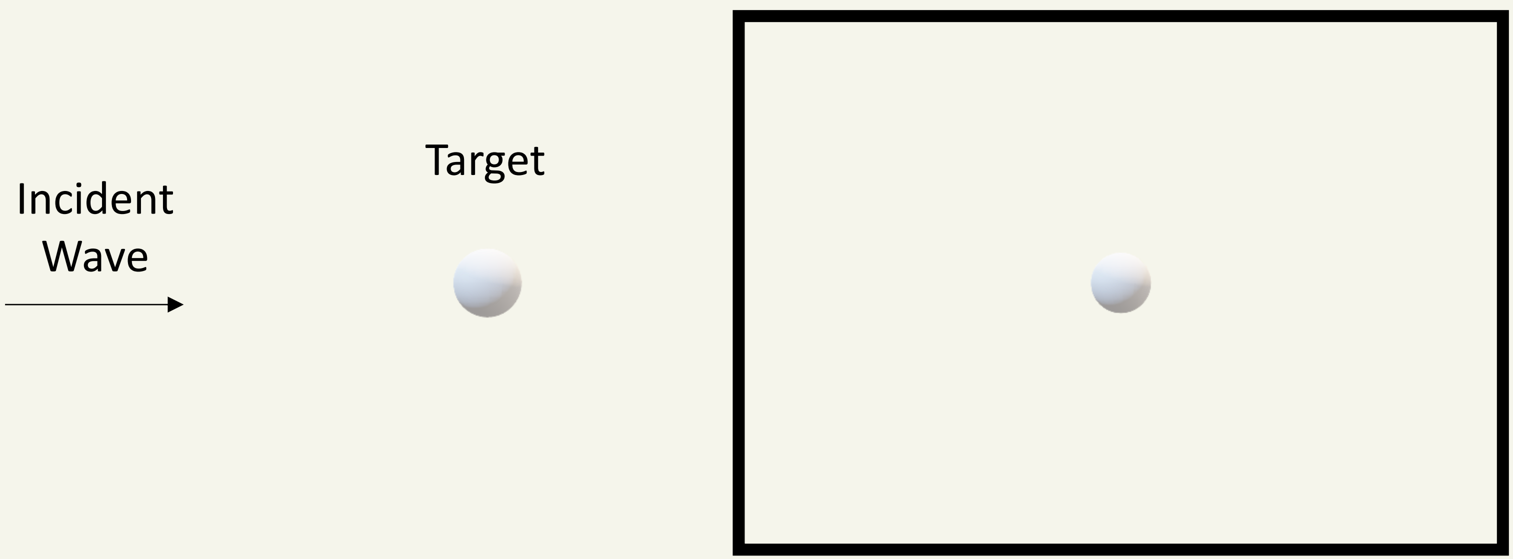
Clutter: A stochastic echo field generated by a large ensemble of weak, randomly placed scatterers (e.g., leaves). Echoes are variable and modeled as a random process characterized by statistical properties (e.g., leaf density, orientation, size), not exact waveforms.

What Is A Deterministic Target?

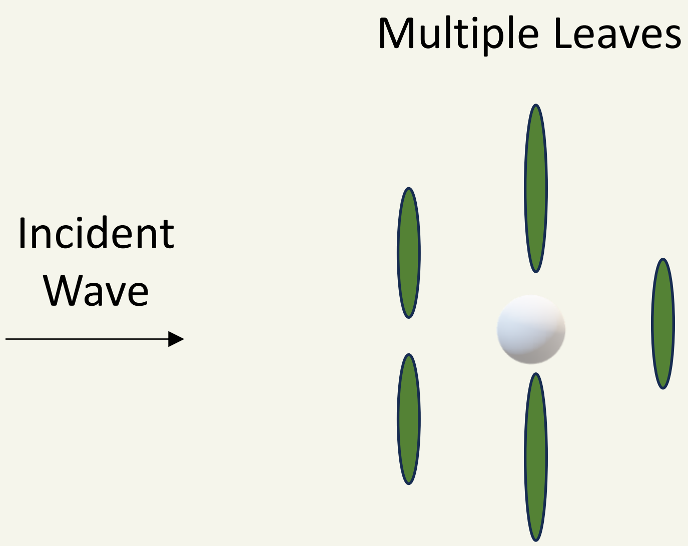
For A Single Target
The Total Received Echo from Target:

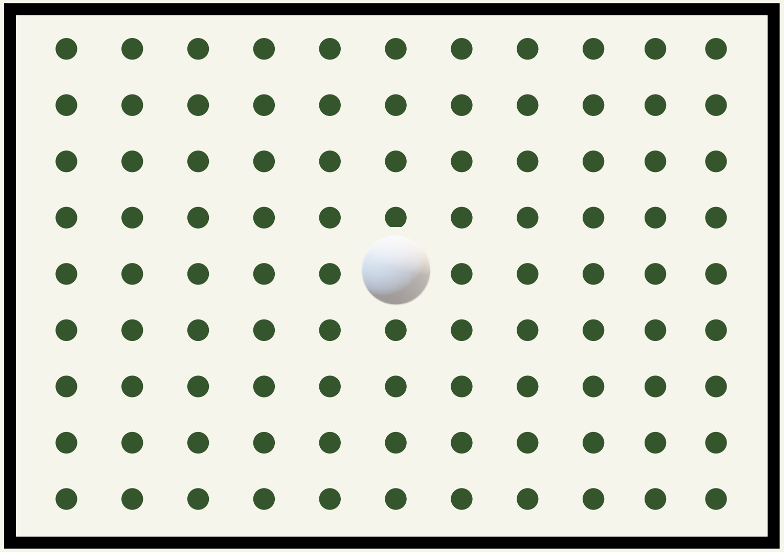
$$P_{r_t} = P_t \frac{\sigma_t(\theta_t)}{(4\pi r_t^2)^2} e^{-2\alpha(f) r_t}$$

- Target geometry & material are fixed
- Echo shape, timing, and amplitude are consistent
- Example: rigid sphere or flat reflector
- Orientation matters, but variation is minimal over time



Now Combining Clutter and a Deterministic Target

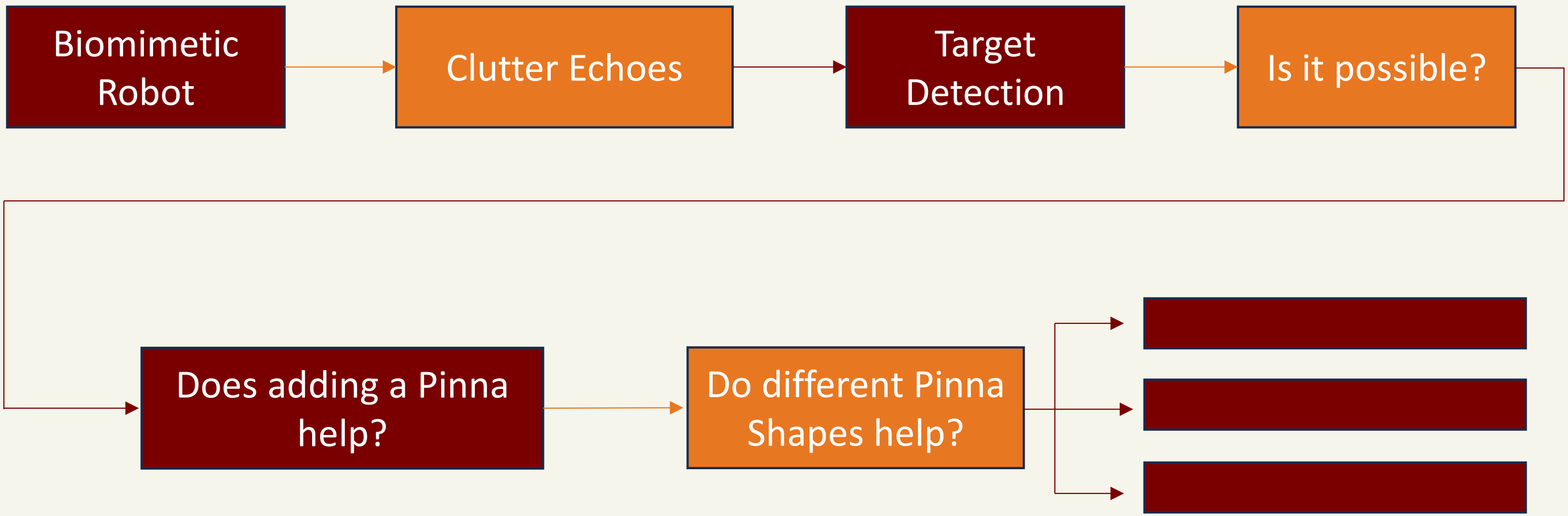




VIRGINIA TECH

My Contribution:

- Different pinna shapes impart distinct acoustic cues about the environment; Machine Learning can extract this information.



Motivate Pilot Data

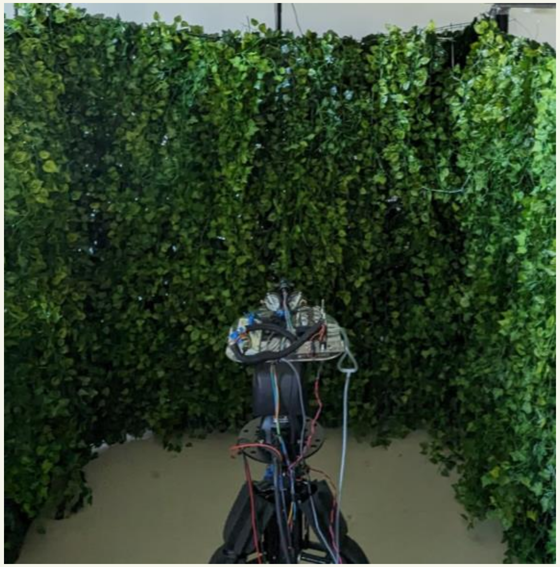
Can Machine Learning help?

Example Spec of No Target

Example Spec of Target

Is it possible to Detect A Target in Clutter?

No Target



Target Fully Embedded

- **Target:** Large Metal Plate, 30 cm radius
- **Classes:** No Target, Target Fully Embedded
- **Shapes:** No Pinna vs Pinna
- Pan-Tilt Unit Operated
  - Azimuth = -5°:1°:5°
  - Elevation = -3°:1°:3°
- **1,000 echoes** per **class**

- **Network:** Shallow 2D CNN, Fixed
- **STFT Parameters:** Fixed
- **Transmit Amplitude:** Fixed, Maximum
- **Transmit Signal:** 2ms Chirp, **60kHz to 40kHz**
- **Validation Method:** k-Folds, k = 5

Yes, it’s Possible

Dataset: 1,000 samples/class

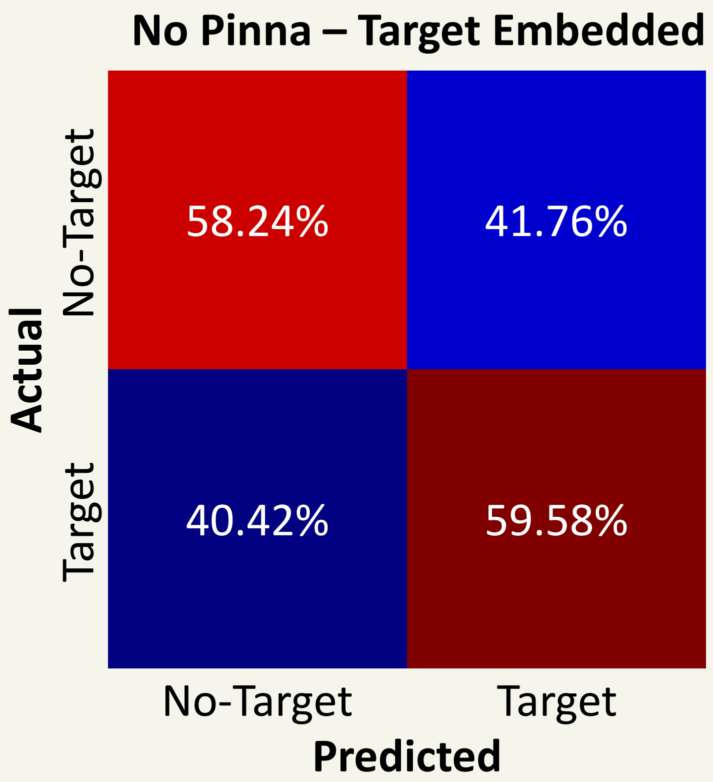
Train: 600 samples/class

Test: 200 samples/class

Validation: 200 samples/class

Averaged Confusion Matrix over k-Folds

k-Folds Validation, k = 5



58.91%

Does Adding A Pinna Help?

Dataset: 1,000 samples/class

- Train: 600 samples/class
- Test: 200 samples/class
- Validation: 200 samples/class

Averaged Confusion Matrix over k-Folds

k-Folds Validation, k = 5

↑ 7.02%

No Pinna – Target Embedded

Actual \ Predicted	No-Target	Target
No-Target	58.24%	41.76%
Target	40.42%	59.58%

58.91%

Pinna – Target Embedded

Actual \ Predicted	No-Target	Target
No-Target	67.89%	32.11%
Target	36.24%	63.76%

65.83%

Do Different Shapes Perform Differently in Different Regions?

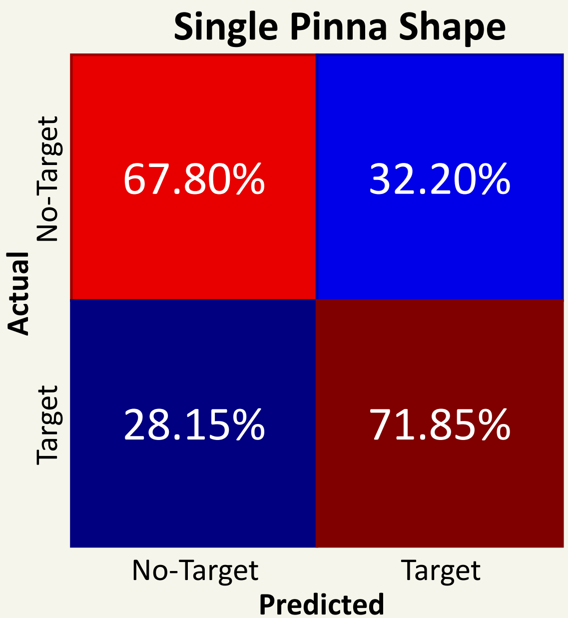
Shape 1

Shape 2

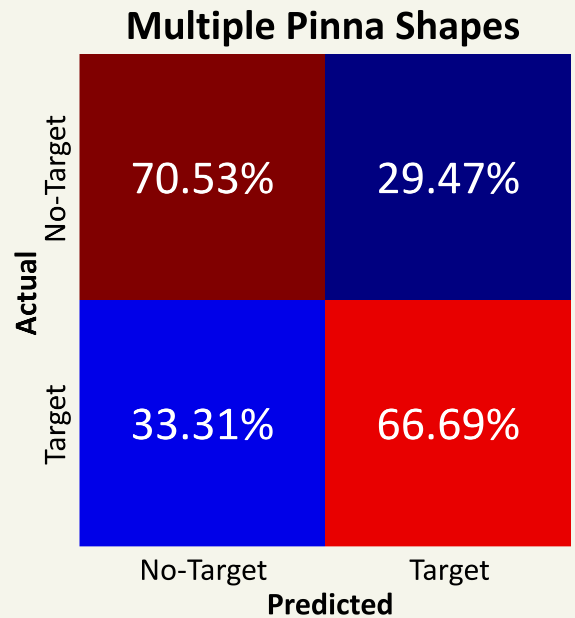
Indicating it may not **only** about Pinna Shape Gain

VIRGINIA TECH

Does Adding Multiple Static Pinna Shapes Help?



69.83%



68.61%

Single Shape
1,000 samples/class
No Target vs Target

Two Shapes
1,000 samples/class
No Target – Shape 1 (500 samples)
No Target – Shape 2 (500 samples)
Target – Shape 1 (500 samples)
Target – Shape 2 (500 samples)

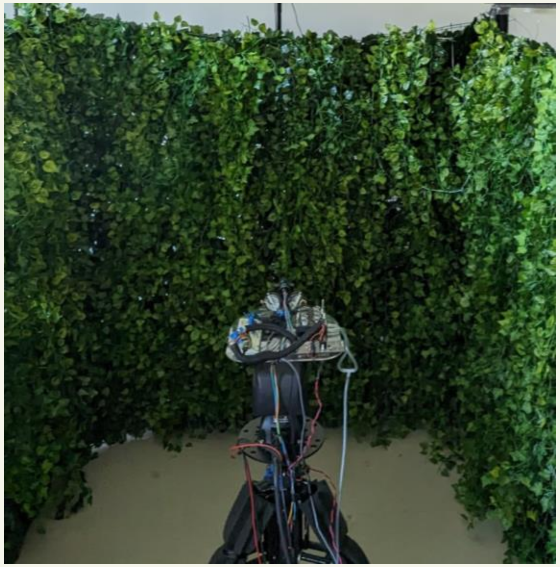
No Target vs Target

Indicating it's not **<u>only</u>** about Pinna Shape

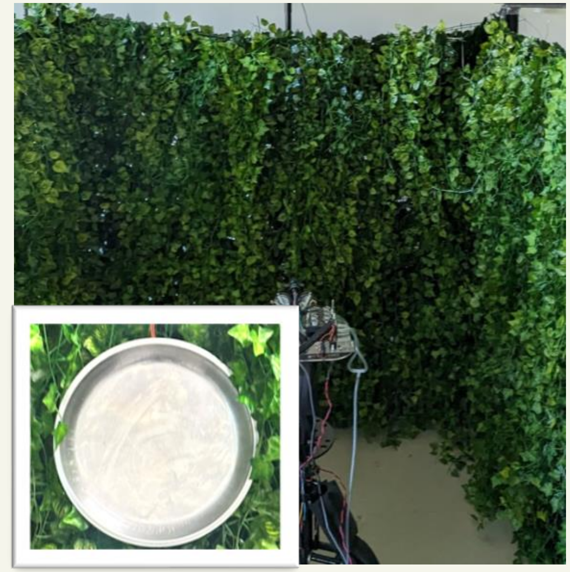
VIRGINIA TECH

Increasing the Bandwidth: Is it possible to Detect A Target in Clutter?

No Target



Target Fully Embedded



- **Target:** Large Metal Plate, 30 cm radius
- **Classes:** No Target, Target Fully Embedded
- **Shapes:** No Pinna vs Pinna
- Pan-Tilt Unit Operated
    - Azimuth = -5°:1°:5°
    - Elevation = -3°:1°:3°
- **1,000 echoes** per **class**

- **Network:** Shallow 2D CNN, Fixed
- **STFT Parameters:** Fixed
- **Transmit Amplitude:** Fixed, Maximum
- **Transmit Signal:** 2ms Chirp, 80kHz to 20kHz
- **Validation Method:** k-Folds, k = 5

Does Adding Bandwidth Help?

No Pinna – Target Embedded

Actual \ Predicted	No-Target	Target
No-Target	69.50%	30.50%
Target	30.43%	69.57%

60 kHz Bandwidth

69.35%

Bandwidth Constant
Adding a Pinna

↑13.89%

Pinna – Target Embedded

Actual \ Predicted	No-Target	Target
No-Target	86.16%	13.84%
Target	19.69%	80.31%

60 kHz Bandwidth

83.24%

Pinna – Target Embedded

Actual \ Predicted	No-Target	Target
No-Target	67.89%	32.11%
Target	36.24%	63.76%

20 kHz Bandwidth

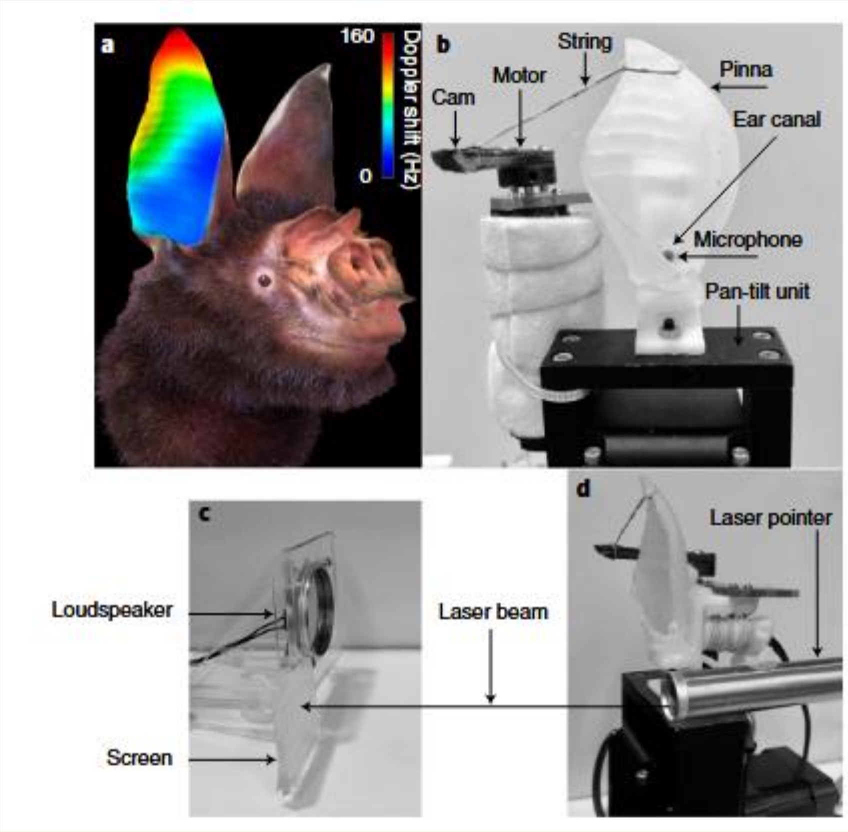
65.83%

↑17.41%

Pinna Constant
Adding Bandwidth

Would Adding A Moving Pinna Help?

- Prior work demonstrated that Doppler signatures induced by deforming pinnae encode directional information with sub-degree precision.
- These signatures emerge even when the source is stationary, validating the idea that receiver motion alone can introduce useful Doppler structure.
- Can we use this as well?



Hypothesis: Decorrelation via Doppler

- Traditionally, Doppler is introduced through **target motion**.
- Introduce a Doppler on the Receiver (Pinna) Side
- This may cause the target to exhibit a non-zero Doppler shift
  - **Target Echo shifts coherently** → sharp Doppler peak
- While clutter remains near zero
  - **Clutter Echo shifts incoherently** → a spread of small Doppler shifts
  - Potentially because the position of the clutter discs (foliage) is random, hence the relative motion wrt. the pinna motion will decorrelate the clutter doppler
- This could create separation where the target becomes distinguishable from clutter that previously overlapped in range only.
- Explore this mechanism, dynamic, and hypothesis

References

[1] Todd, B. D., & Müller, R. (2018). A comparison of the role of beamwidth in biological and engineered sonar. *Bioinspiration & Biomimetics, 13*(1), 016014. https://doi.org/10.1088/1748-3190/aa9a0f

[2] Jacobs, D. S., & Bastian, A. (2016). Bat Echolocation: Adaptations for Prey Detection and Capture. In *Predator–Prey Interactions: Co-evolution between Bats and Their Prey* (pp. 13–30). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-32492-0_2

[3] Yin, X., Qiu, P., Yang, L., & Müller, R. (2017). Horseshoe bats and Old World leaf-nosed bats have two discrete types of pinna motions. *The Journal of the Acoustical Society of America, 141*(5), 3011-3017. https://doi.org/10.1121/1.4982042

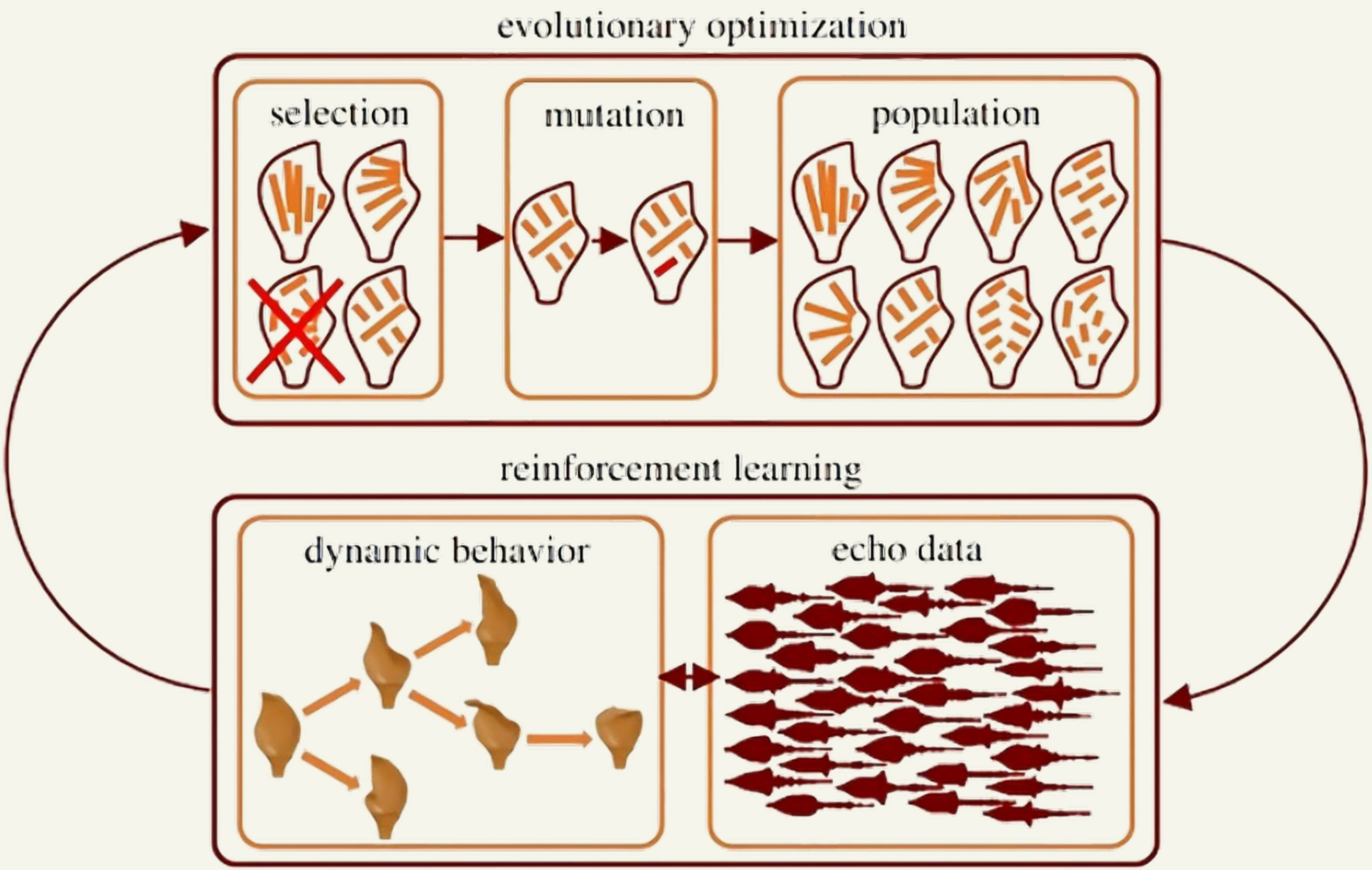
[4] Müller, R., Gupta, A. K., Zhu, H., Pannala, M., Gillani, U. S., Fu, Y., Caspers, P., & Buck, J. R. (2017). Dynamic Substrate for the Physical Encoding of Sensory Information in Bat Biosonar. *Physical Review Letters, 118*(15), 158102. https://doi.org/10.1103/PhysRevLett.118.158102

[5] Geberl, C., Kugler, K., & Wiegrebe, L. (2019). The spatial resolution of bat biosonar quantified with a visual-resolution paradigm. *Current Biology, 29*(11), 1842–1846. https://doi.org/10.1016/j.cub.2019.04.046

[6] Simmons, J. A. (1971). Echolocation in bats: Signal processing of echoes for target range. *Science, 171*(3974), 925–928. https://doi.org/10.1126/science.171.3974.925

Back-Up Slides

Deterministic Target Detection & Localization



A Reinforcement Learning Problem

Shape 1

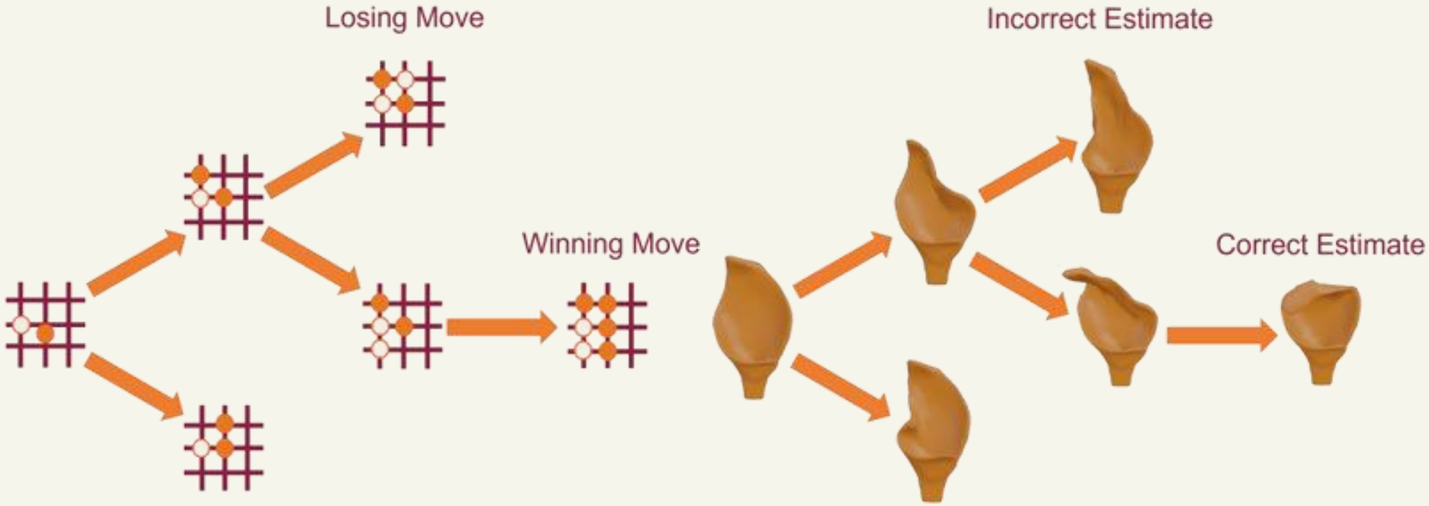
R1	R2	R3
R4	R5	R6
R7	R8	R9

Shape 2

R1	R2	R3
R4	R5	R6
R7	R8	R9

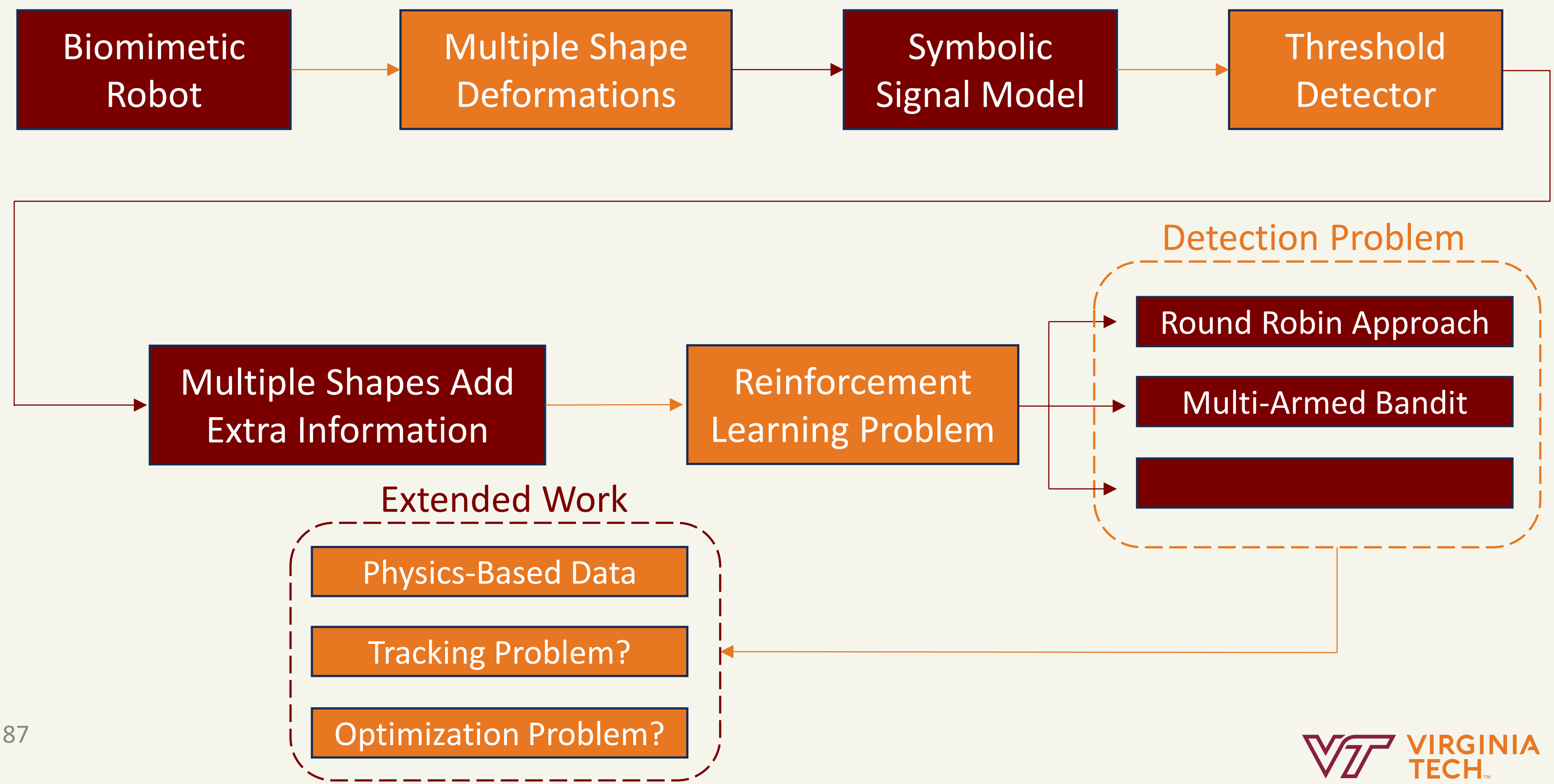
Shape 3

R1	R2	R3
R4	R5	R6
R7	R8	R9



My Contribution: Reinforcement Learning Might Be The Key

- Different pinna shapes impart distinct acoustic cues about the environment; Machine Learning can extract this information. Reinforcement Learning can learn the policy to utilize this information for down-stream tasks.

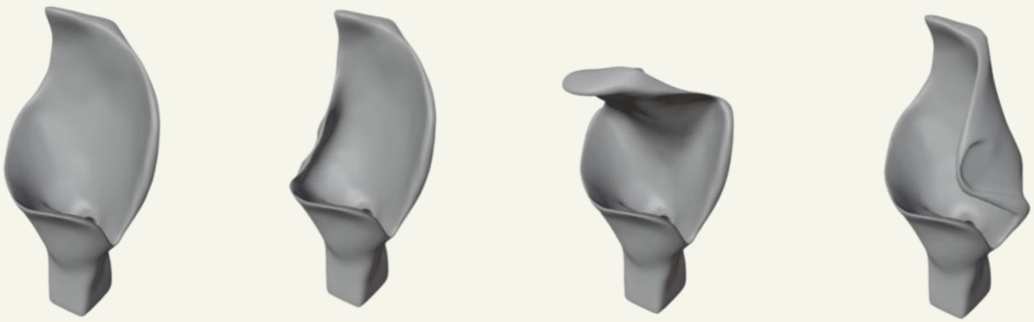


An Active Learning Approach: RL Multi-Armed Bandit

Scenario: At each time step N, choose a pinna shape i to detect a target in a specific region. A reward is given based on whether the detection was correct and whether the selected shape was optimal.

Problem: Over N time steps, maximize total detection performance by learning which shapes work best in which regions.

Exploration vs Exploitation: Which Pinna Shape i is best for this Region? Should I try a new one? Or stick to what I know?

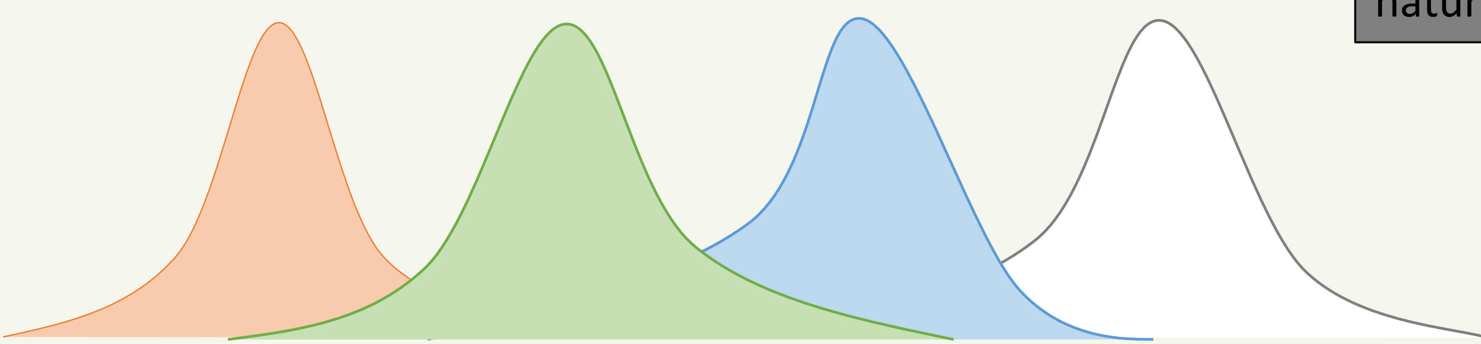


Shape 1 (0, 0, 0)

Shape 2 (10, 0, 0)

Shape 3 (0, 10, 0)

Shape 4 (0, 0, 10)



"Add a small bandit-arm icon or RL decision flow (circle + arrow + reward icon) to emphasize the RL nature."