ADAPTIVE BASIS SELECTION FOR COMPRESSED SENSING IN ROBOTIC TACTILE SKINS

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Introduction

Robotic tactile skins are networks of tiny sensing elements that cover the surface of a robot. They are beneficial in whole-body manipulations, human-robot communication, environmental understanding, and safe interactions. Due to hardware challenges, it may not be feasible to poll each sensor individually. Thus, we applied compressed sensing techniques to data acquisition and processing in robotic tactile skins [1]. Compressed sensing relies on the signals being approximately sparse in some basis, but, as shown in the following table, we found that different signals were sparse in different bases.

Approximate Sparsity: Number of Elements Greater Than 0.001										
Object	N	Haar		Daubechies 4		DCT		Contourlet		
		Mean	Max	Mean	Max	Mean	Max	Mean	Max	
Golf Ball	4096	95.9	146	93.1	152	148.4	203	**17.4**	**23**	
Granola Box	4096	**95.3**	**209**	206.5	357	360.2	602	426.4	658	
Drill	4096	176.4	265	178.1	250	176.1	235	**111.6**	**144**	
Cup	4096	353.2	462	351.3	451	404	522	**164.4**	**221**	
Clamp	4096	310	425	238.5	329	222.9	291	**139.9**	**185**	

Problem Statement: *Given a compressed signal* $\mathbf{y}$ *and a set of candidate bases, is it possible to automatically select the basis* Ψ *that most accurately reconstructs the original signal* $\mathbf{x}$*?*

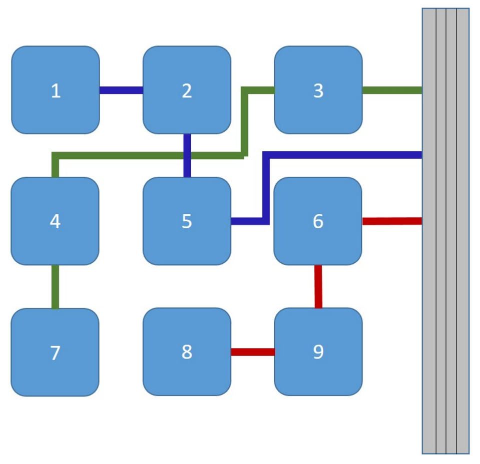
Background: Compressed Sensing

Compression:

- During acquisition process
- Hardware implementations
- Measurements:

$$\mathbf{y} = \Phi\mathbf{x} = \Phi\Psi\mathbf{s} = A\mathbf{s},$$

where $\mathbf{x}$ is signal of interest,
Ψ is the basis such that $\mathbf{x} = \Psi\mathbf{s}$,
and Φ is the measurement matrix



Reconstruction:

- Mathematical approach

$$\hat{\mathbf{s}} = \operatorname*{argmin}_{\mathbf{s}} \tfrac{1}{2}\|A\mathbf{s} - \mathbf{y}\|_2^2 + \lambda\|\mathbf{s}\|_1$$
$$\hat{\mathbf{x}} = \Psi\hat{\mathbf{s}}$$

- GPU implemented solver for 100 Hz reconstruction rate

Acknowledgements

This work was partially supported by NSF Grants CNS-1553340, CNS-1527287, and NRI-1537023. B. Hollis is supported by a SMART Scholarship.

Our Approach: Adaptive Basis Selection

Train a classifier to select which basis to use to reconstruct each signal. Training set consists of pairs compressed signals and labels $(\mathbf{y}_i, \ell_i)$, where the labels correspond to bases. We explored two types of labels:

Labeling Method 1 - Reconstruction Accuracy:

- Requires applied force $\mathbf{x}$
- Peak Signal to Noise Ratio (PSNR):

$$\mathrm{F}_{PSNR}\Big(\hat{\mathbf{x}}, \mathbf{x}, \mu\Big) = 10\log_{10}\frac{\mu^2}{\frac{1}{n}\|\mathbf{x}-\hat{\mathbf{x}}\|_2^2},$$

where μ is the upper bound of x_i.

- $\ell_i = \Psi_j$ that maximizes PSNR

Labeling Method 2 - Compressibility:

- Accepts sensed force $\tilde{\mathbf{x}}$
- Compressibility:

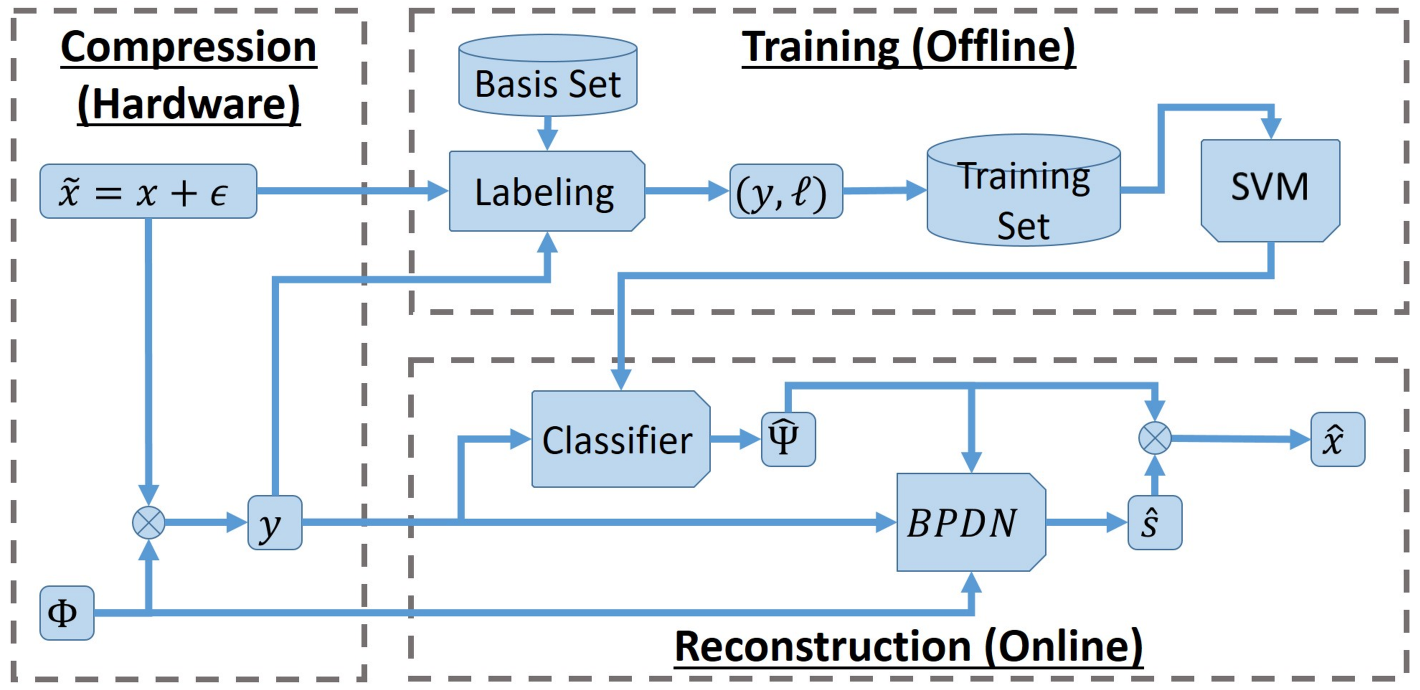
$$\kappa(\Psi, \tilde{\mathbf{x}}) = \|\Psi\tilde{\mathbf{s}} - \Psi\tilde{\mathbf{s}}_k\|_1,$$

where $\tilde{\mathbf{s}}_k$

- $\ell_i = \Psi_j$ that minimizes $\kappa(\Psi, \tilde{\mathbf{x}})$

Classifier:

- Linear classifier
- Algorithm:
  Support Vector Machine (SVM)
- Input:
  Compressed signals $\mathbf{y}$
- Output:
  Basis $\hat{\Psi}$



Experiments

Data Set

- Simulated tactile signals
- 16 objects
- 10 orientations, 36 translations, 4 force levels
- 23,040 signals
- 64x64 taxel array ($n = 4096$)
- Training Set: 4 objects (5,760 signals)
- Validation Set: 1/3 Training Set
- Test Set: Remaining 12 objects (17,280 signals)

Compressed Sensing Parameters

- Basis Set:
  - Haar Transform
  - Contourlet Transform
- Measurement Matrix:
  Scrambled Block Hadamard Ensemble [2]
- Reconstruction algorithm:
  Fast Iterative Shrinkage-Thresholding Algorithm [3]

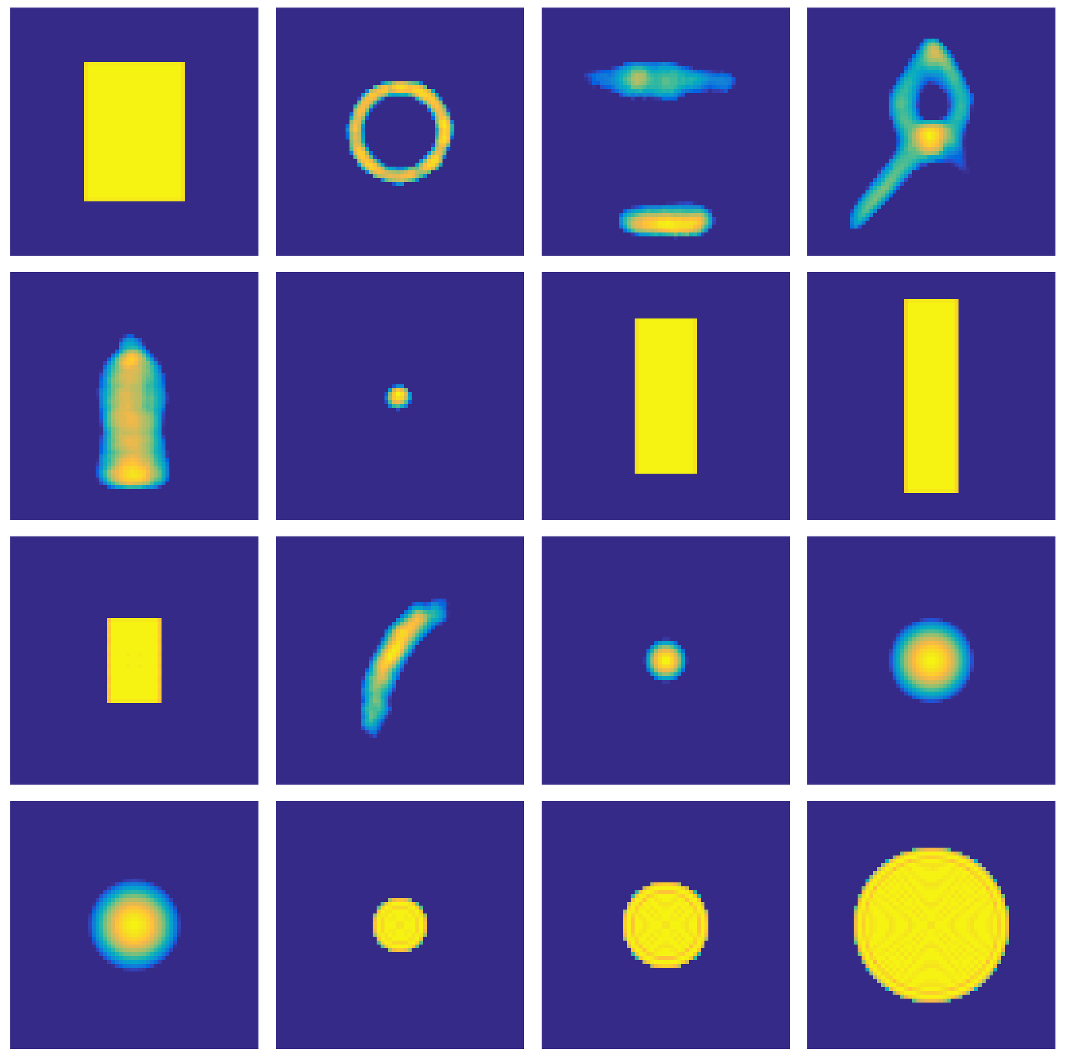


Figure 1: Example noise-free tactile signals for each object. The color scale goes from dark blue (no contact deformation) to yellow (contact deformation of 0.01 units).

Results

- Generally outperforms single basis (Fig. 2)
- Performs similar to perfect oracle (Fig. 2)
- Up to 9 dB improvement over single basis (Fig. 3)

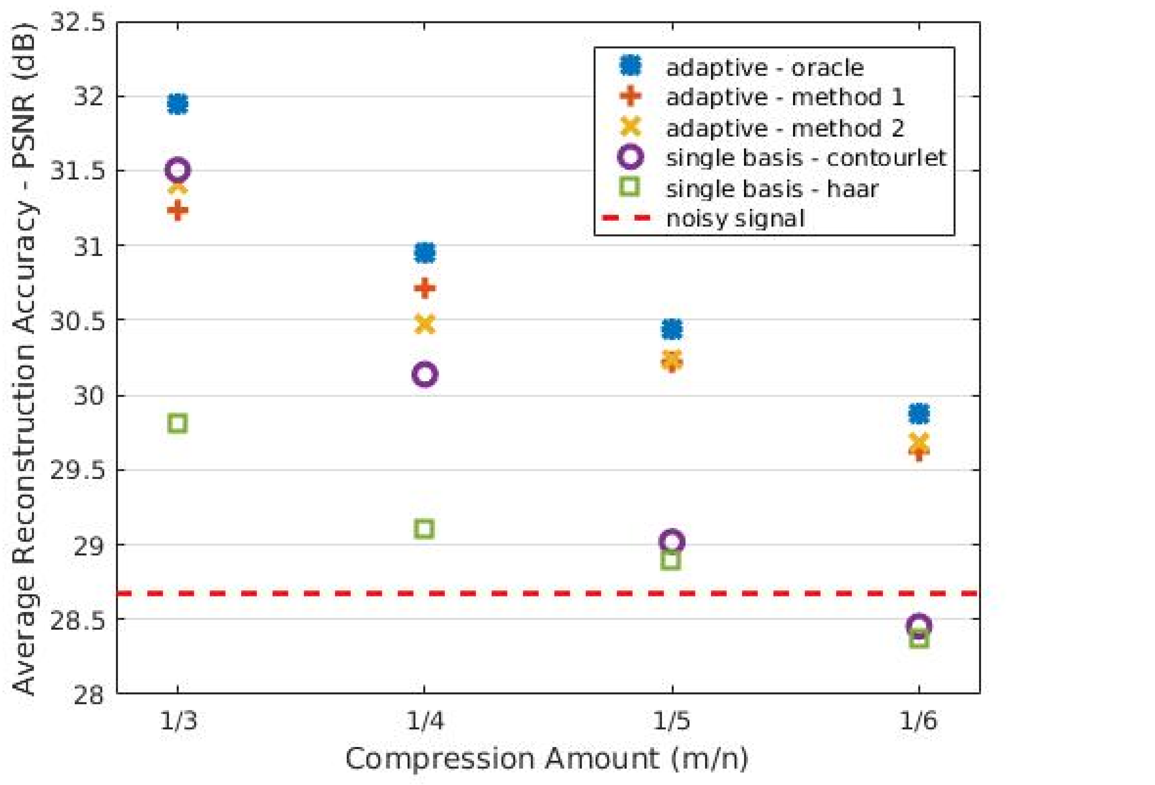


Figure 2: The average PSNR of the various basis selection methods for different levels of compression.

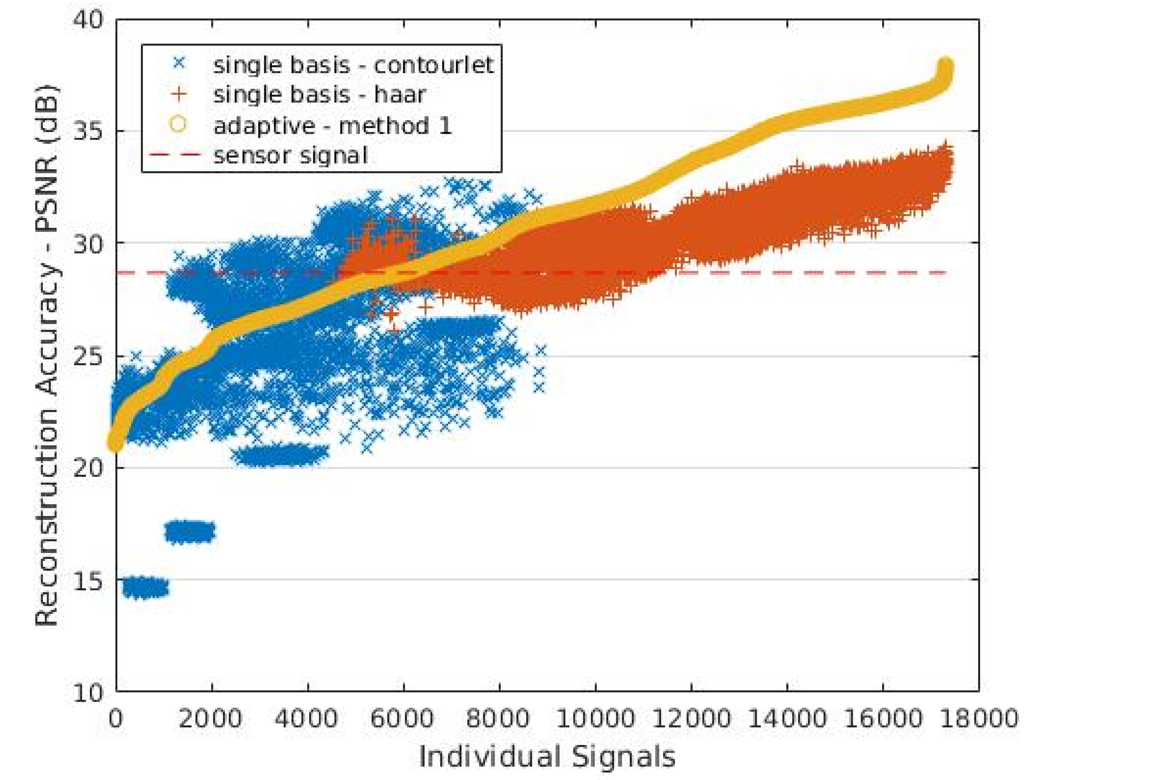


Figure 3: The PSNR for each signal in the test set, when reconstructed using different bases from $m = n/4$ measurements. The signals are sorted in ascending order by the PSNR of the our adaptive-basis reconstructions.

References

[1] B. Hollis, S. Patterson, and J. Trinkle, “Compressed Sensing for Tactile Skins,” in *IEEE Int. Conf. Robot. Autom.*, 2016, pp. 150–157.

[2] L. Gan, T. T. Do, and T. D. Tran, “Fast compressive imaging using scrambled block Hadamard ensemble,” in *Eur. Signal Process. Conf.*, aug 2008, pp. 1–5.

[3] A. Beck and M. Teboulle, “A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems,” *SIAM Jour. on Imaging Sci.*, vol. 2, no. 1, pp. 183–202, 2009.