DIRECT INFERENCE ON COMPRESSIVE MEASUREMENTS USING CONVOLUTIONAL NEURAL NETWORKS

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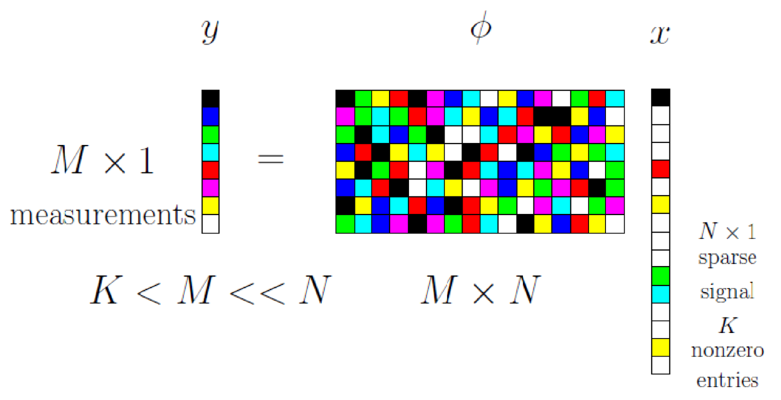
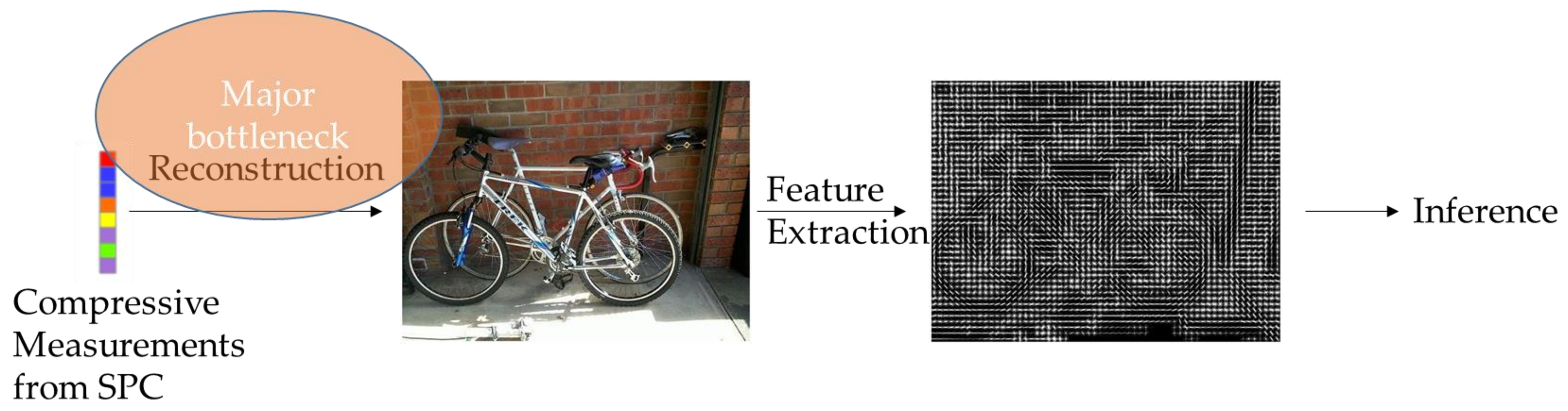
Compressive Sensing (CS)



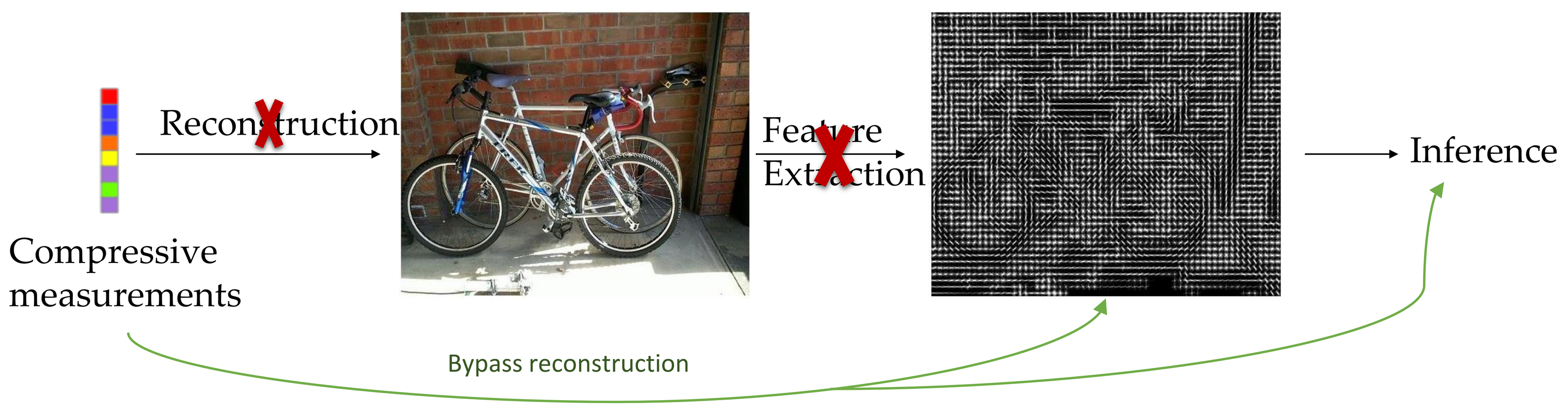
- The Single-Pixel Camera (SPC) is a popular example of a compressive imager.

Traditional Pipeline – Reconstruct-then-infer



- Recovering x from y is ill-posed but possible if x is sparse and MR (M/N) is sufficiently large.
- Most algorithms are iterative in nature and are computationally expensive. The reconstruction quality is also poor at low measurements rates of 0.1.

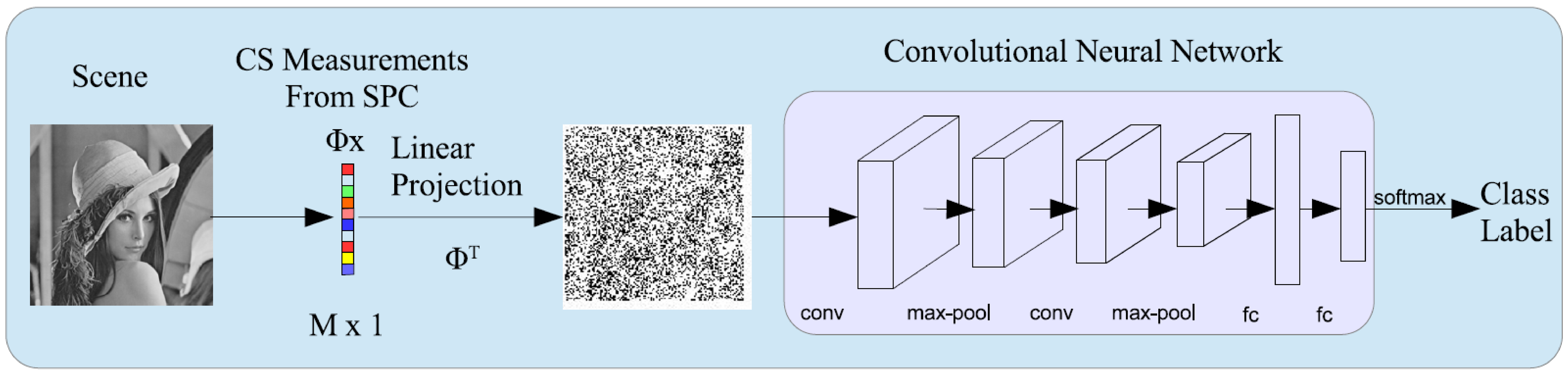
Reconstruction-free Feature Extraction/Inference



- Dimensionality-reduced matched filters – Smashed Filters [1]
  - Not robust to input variations.
  - Johnson – Lindenstrauss lemma is used to perform detection directly in the compressed domain.
  - Computationally much faster than reconstruct-then-infer paradigm.
- Dimensionality reduced correlation filters – Smashed Correlation Filters [2][3]
  - Utilizes J-L lemma to extract features directly without reconstruction.
  - More robust to input variations but cannot handle changes in pose and lighting since the features are still linear.
  - Although faster than reconstruct-then-infer, still computationally inefficient since the test image needs to be correlated with the template filter for each class.

Direct Inference Using Convolutional Neural Networks

- Project measurements back to the pixel space, which allows us to use the same CNN architectures designed for image recognition.
- Train a deep network on the "pseudo-images" to output the class labels.
- Computationally more efficient than smashed correlation filters since a single forward pass is sufficient to determine the class label.
- Possible to learn linear projection step (currently fixed to Φ^T) jointly with the remaining layers.



Experimental Results

MNIST Hand-written digit database

- Grayscale images of hand-written digits (0 - 9)
- Image size = 28 x 28 (784 pixels)
- 50000 training images, 10000 testing images
- Φ is a random Gaussian matrix of size **m x 784**
- CNN architecture based on LeNet-5 [4]

Measurement Rate (MR)	Number of Measurements (m)	Test Error (%)	
		Smashed Correlation Filters [3]	Our Method
1 (Oracle)	784	13.86	0.89
0.25	196	27.42	1.63
0.10	78	43.55	2.99
0.05	39	53.21	5.18
0.01	8	63.03	41.06

ImageNet Database

- RGB images belonging to 1000 classes
- 1.2 million training images and 50000 test images of size 256 x 256
- Φ is a low rank column permuted Hadamard matrix (approximating a Bernoulli matrix) of size **m x 65536**. Measurements are computed using Fast Walsh-Hadamard Transform.
- CNN architecture is based on AlexNet [5] – consists of 5 convolutional layers and 2 fully connected layers.

Measurement Rate (MR)	Number of Measurements (m)	Accuracy (%)
1 (Oracle)	65536	56.88
0.25	16384	39.22
0.10	6554	29.84

[1] Mark A Davenport, Marco F Duarte, Michael B Wakin, Jason N Laska, Dharmpal Takhar, Kevin F Kelly, and Richard G Baraniuk, "The smashed filter for compressive classification and target recognition," in Electronic Imaging. International Society for Optics and Photonics, 2007, pp. 64980H–64980H
[2] K. Kulkarni and P. Turaga, "Reconstruction-free action inference from compressive imagers," Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. PP, no. 99, 2015.
[3] Suhas Lohit, Kuldeep Kulkarni, Pavan Turaga, Jian Wang, and Aswin C. Sankaranarayanan, "Reconstruction-free inference on compressive measurements," in 4th Intl. Conf. on Computational Cameras and Displays, held in conjunction with IEEE CVPR, June 2015.
[4] Yann LeCun, Leon Bottou, Yoshua Bengio, and Patrick ´ Haffner, "Gradient-based learning applied to document recognition," Proceedings of the IEEE, vol. 86, no. 11, pp. 2278–2324, 1998.
[5] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton, "Imagenet classification with deep convolutional neural networks," 2012, pp. 1097–1105.