Low-Complexity Compressed Analysis in Eigenspace with Limited Labeled Data for Real-Time Electrocardiography Telemonitoring

Kai-Chieh Hsu, *Bo-Hong Cho,*
Ching-Yao Chou and An-Yeu (Andy) Wu

National Taiwan University

ECG Telemonitoring with Edge Computing

- Mobile Telemedicine with Wireless Body Area Network (WBAN) [1]
  - Patient-centered health-care
  - Ubiquitous health-care
- ECG Telemonitoring [2], [3]
  - Record the electrical activity of the heart
  - Standard practice in hospitals for diagnoses
- Edge Computing [4]
  - bandwidth cost saving
  - battery life constraint
  - latency requirement

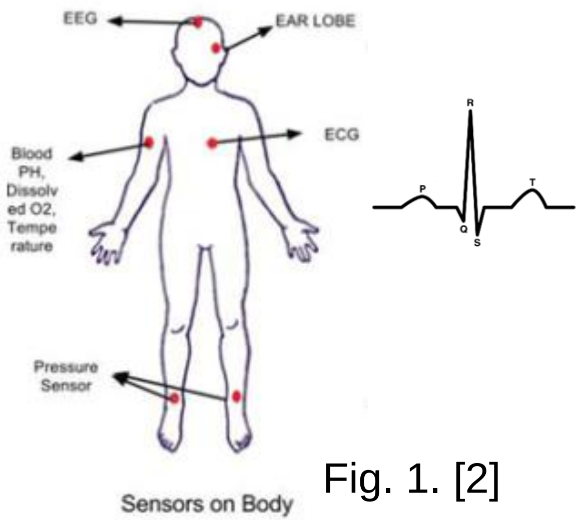


Fig. 1. [2]

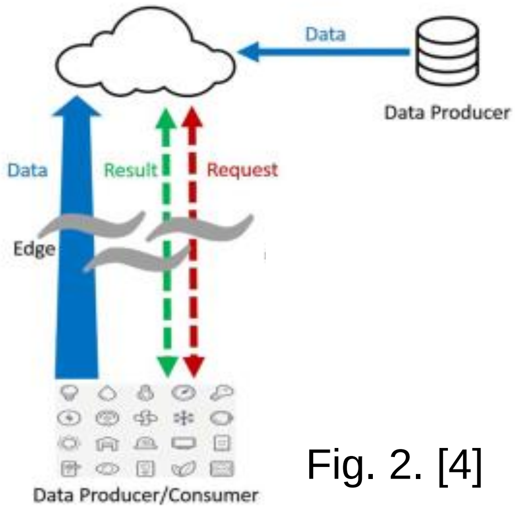
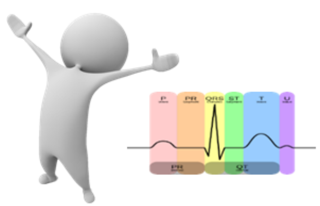


Fig. 2. [4]

Edge Computing under Existing IoT Systems

Wireless Body Area Network



Massive Sampled Data

Transmit

Existing Module

Receive

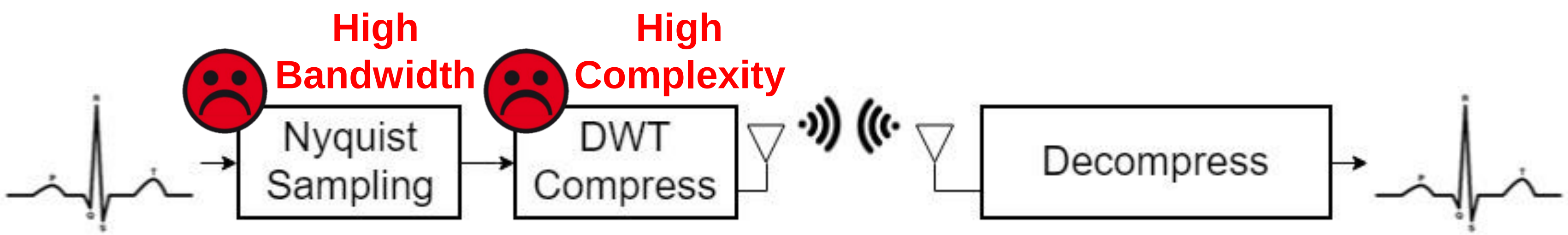
Massive Sampled Data

Machine Learning

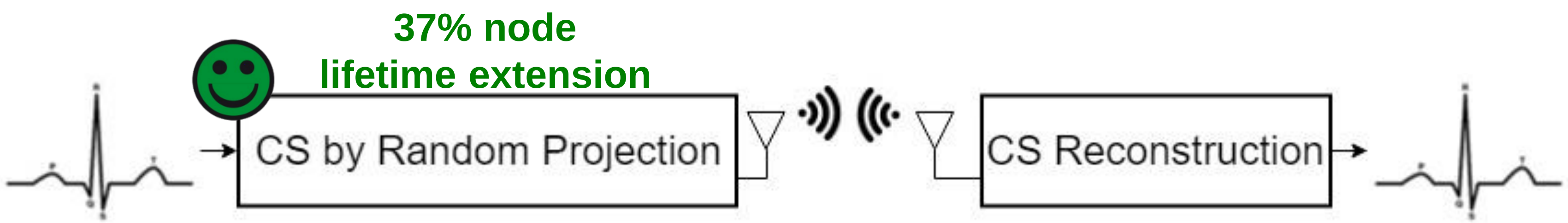
Edge-Devices

Compressed Sensing for ECG Telemonitoring

- Problems of Digital Wavelet Transform (DWT)
  - High bandwidth incompatible to ADC (Nyquist sample rate)
  - High Computational Complexity (Compression)



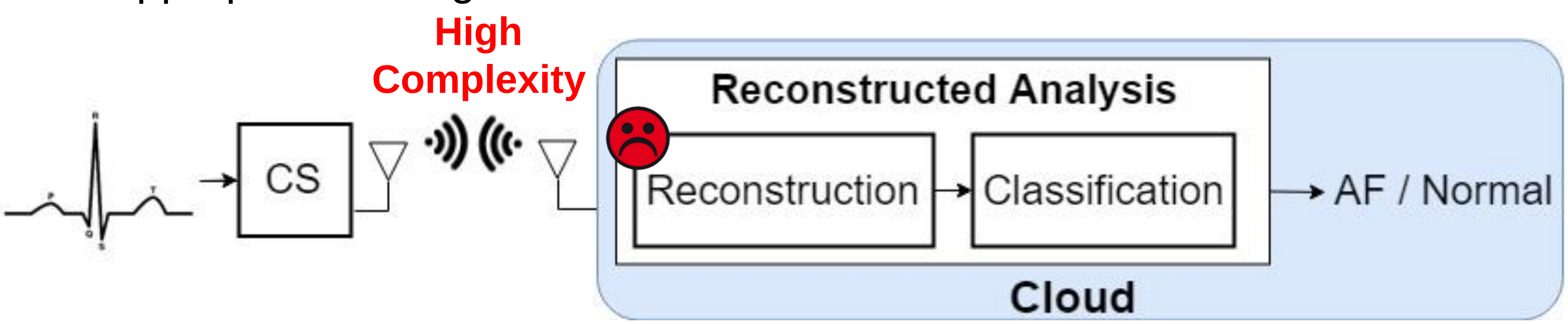
- Compressed sensing (CS) combines sampling and compressing
  - Reduce cost and latency in sampling
  - CS-based sensors achieves a **37%** node lifetime extension [2]



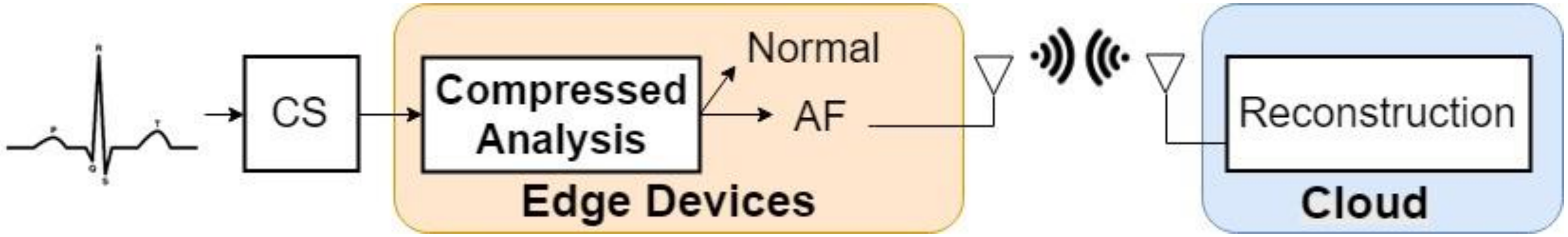
Compressed Analysis for ECG Telemonitoring

- Reconstructed Analysis (RA)
  - High computational complexity because of CS reconstruction algorithms
  - Inappropriate at edge devices.

AF: Atrial Fibrillation

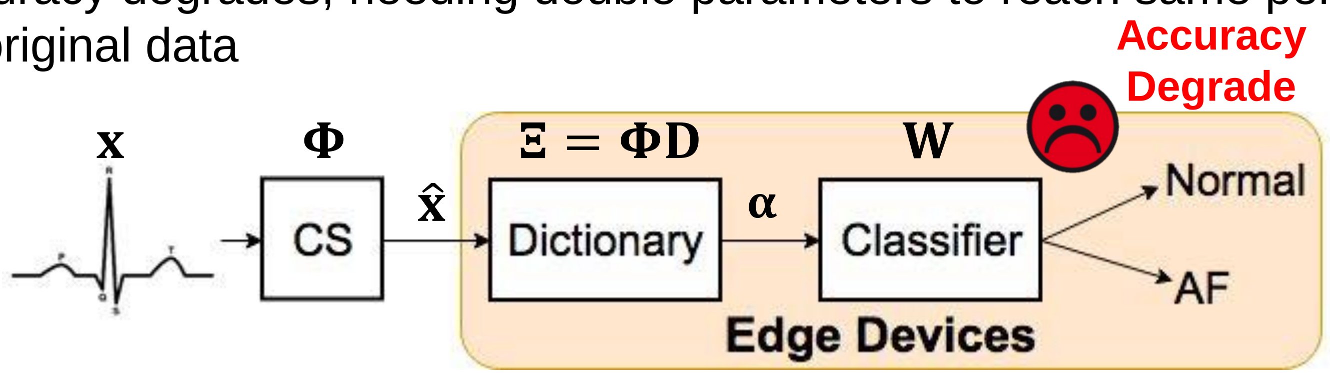


- Compressed Analysis (CA)
  - Reduce power (classification on compressed signals), suitable at edge devices
  - Reduce the bandwidth requirement (only transmitting AF signals)



Naïve CA (CA-N)

- Combining CS with Task-Driven Dictionary Learning (TDDL)
  - What is TDDL [5]
    - Learning a dictionary ($\mathbf{D}$) to provide predictive sparse coding ($\boldsymbol{\alpha}$) at given data set
    - Learning a classifier ($\mathbf{W}$) to classify by the sparse coding $\boldsymbol{\alpha}$
  - Why we choose TDDL?
    - Low Complexity → Overcome battery constraint and bandwidth scarcity
    - High Generalization → Limited label of ECG dataset
- The on-line inference mode of CA-N
  - $\mathbf{D}$ and $\mathbf{W}$ learned on original data ($\mathbf{X}$)
  - Accuracy degrades, needing double parameters to reach same performance on original data



Contribution of Proposed Scheme (1/2)

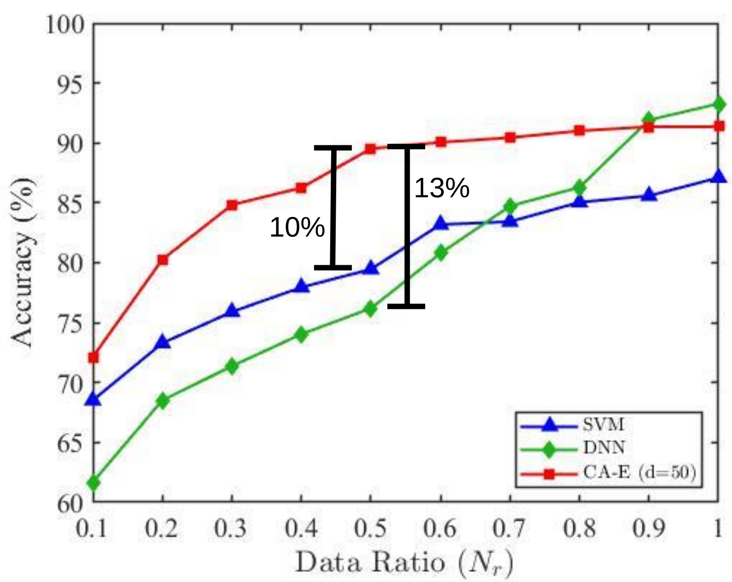
- Low-Complexity (overcame battery and bandwidth requirement)
  - Our proposed Eigenspace-aided Compressed Analysis (CA-E) vs Naïve Compressed Analysis (CA-N)

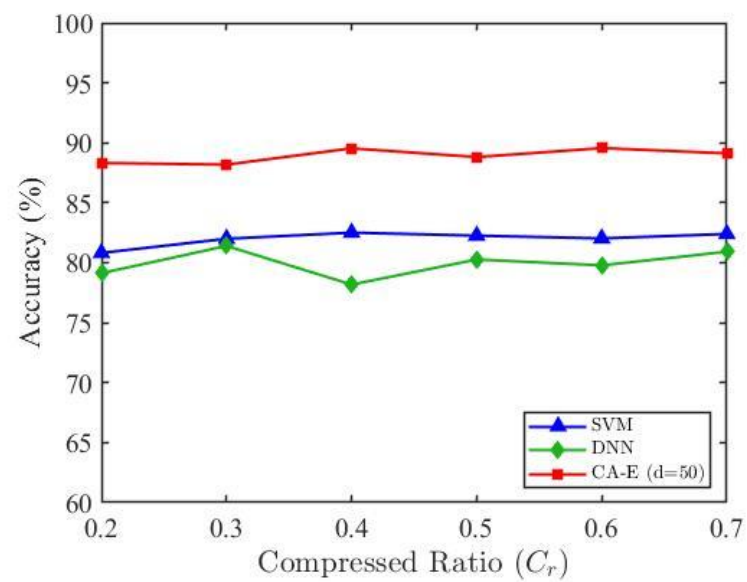
Model	# Parameters	Training Time (s)	Inference Time (ms)	Accuracy (%)
CA-N	13k	452.56	26.94	89.24 ± 0.520
CA-E (Our proposed)	4.25k	107.15	3.50	90.05 ± 0.256

  - Reduce about **67%** parameters (Memory ↓)
  - Reduce about **87%** inference time (Power ↓)
  - Reduce about **76%** training time (Power ↓)

Contribution of Proposed Scheme (2/2)

- High-Stability
  - CA-E outperforms DNN and SVM by over 10% when the amount of data is halved. (Overcame limited label of ECG dataset)
  - CA-E reaches about 90% under all compressed ratio (Stable under all compressed ratio)





Eigenspace-Aided CA (Training)

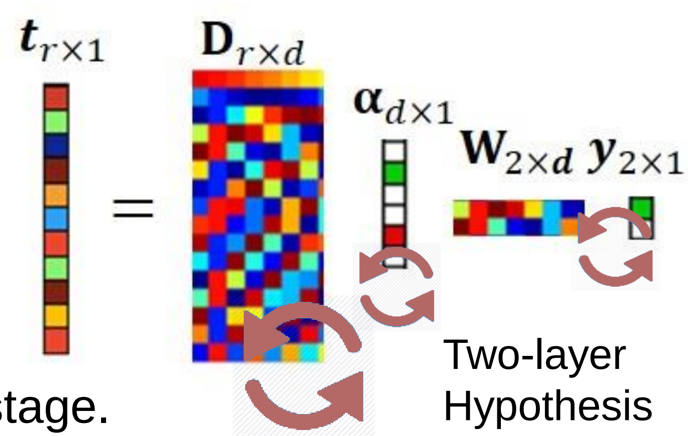
- Principal Component Analysis (PCA)
  - Record mean vector ($\boldsymbol{\mu}$) of dataset ($\mathbf{X}$)
  - Learn eigenspace ($\boldsymbol{\Psi} \in \mathbb{R}^{N\times r}$) of $\mathbf{X}$
  - Transpose to eigenspace by $\mathbf{T} = \boldsymbol{\Psi}^{\mathbf{T}}(\mathbf{X} - \boldsymbol{\mu})$

$$\min_{\alpha,\mathrm{D}} \frac{1}{m}\sum_{i=1}^{m}\frac{1}{2}\|\mathbf{x_i} - \mathbf{D}\boldsymbol{\alpha}\|_2^2 + \lambda\|\boldsymbol{\alpha}\|_1$$

$$\min_{\mathbf{W}} \frac{1}{m}\sum_{i=1}^{m} l_s(\mathbf{y}_i, \mathbf{W})$$

$$\min_{\mathbf{W},\mathbf{D}} \frac{1}{m}\sum_{i=1}^{m} l_s(\mathbf{y}_i, \mathbf{W}, \boldsymbol{\alpha}_{\mathbf{D}}) + \frac{\gamma}{2}\|\mathbf{W}\|_F^2$$

- TDDL to learn $\mathbf{D}$ and $\mathbf{W}$ on $\mathbf{T}$
  - Stage I. Initialize
    - Dictionary: online dictionary learning (ODL) [6]
    - Weight: square / logistic loss
  - Stage II. **Co-optimize $\mathbf{D}$ and $\mathbf{W}$ with labels**
    - Alternates between $\mathbf{A}$ and $\mathbf{D}, \mathbf{W}$
    - Update dictionary with back propagation rule
  - Sparse coding plays an important role in both stage.



$$\boldsymbol{\alpha}_{\mathbf{D}} \triangleq \operatorname*{argmin}_{\alpha\in\mathbb{R}^d} \frac{1}{2}\|\mathbf{x} - \mathbf{D}\boldsymbol{\alpha}\|_2^2 + \lambda\|\boldsymbol{\alpha}\|_1$$

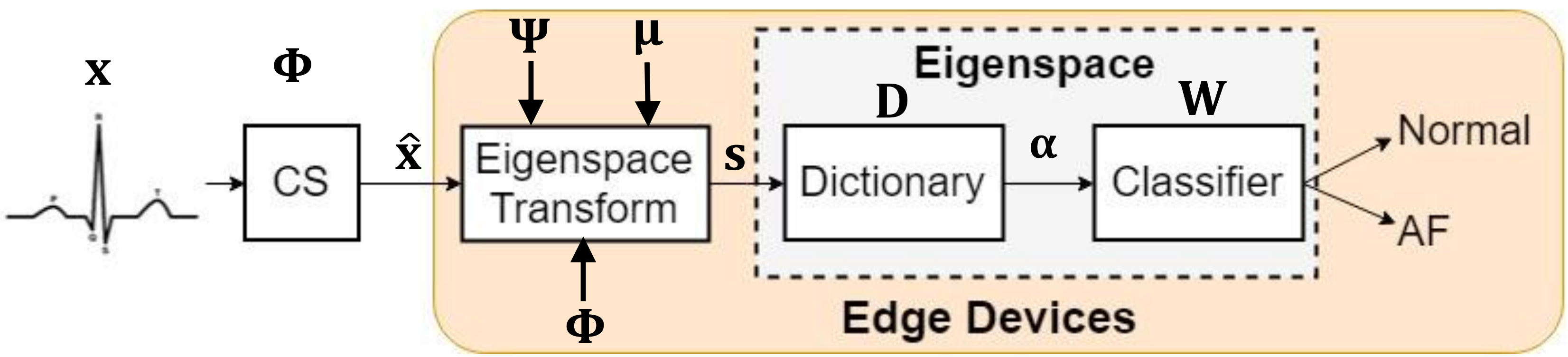
Eigenspace-Aided CA (Inference)

- Eigenspace Transform
  - Compressed sensing signal is transmitted with known sensing matrix ($\mathbf{\Phi}$), the decoding data is obtained by

$$\mathbf{s} = (\mathbf{\Phi\Psi})^{+}(\hat{\mathbf{x}} - \mathbf{\Phi\mu}) = \mathbf{\Theta}^{+}(\hat{\mathbf{x}} - \mathbf{\Phi\mu})$$

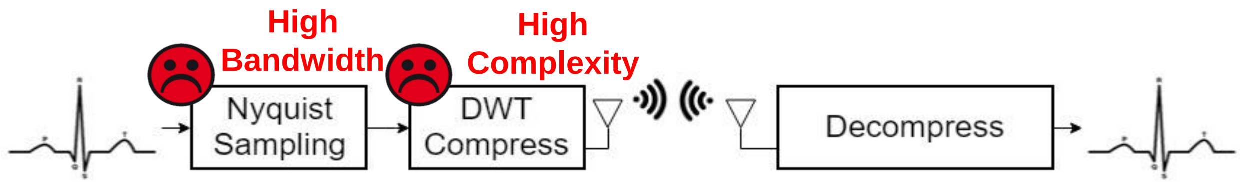
  - $(\quad)^{+}$: pseudo-inverse
- The decoding vector ($\mathbf{s}$) then pass through TDDL-based classifier
  - Get sparse coding $\boldsymbol{\alpha}(\mathbf{s}, \mathbf{D})$
  - Simple linear classifier $\mathbf{W}$

$$\boldsymbol{\alpha}_{\mathbf{D}} \triangleq \underset{\alpha \in \mathbb{R}^d}{\operatorname{argmin}} \frac{1}{2}\|\mathbf{x} - \mathbf{D}\boldsymbol{\alpha}\|_2^2 + \lambda\|\boldsymbol{\alpha}\|_1$$

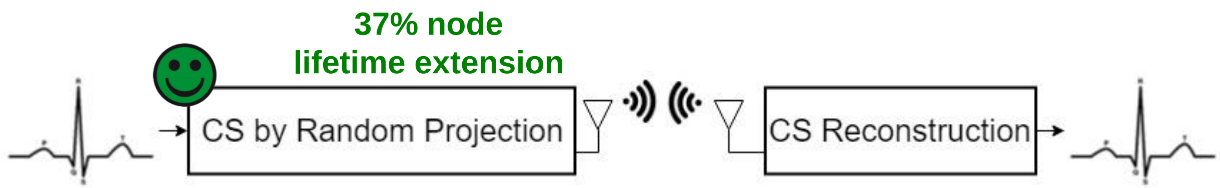


Scheme Development (1/2)

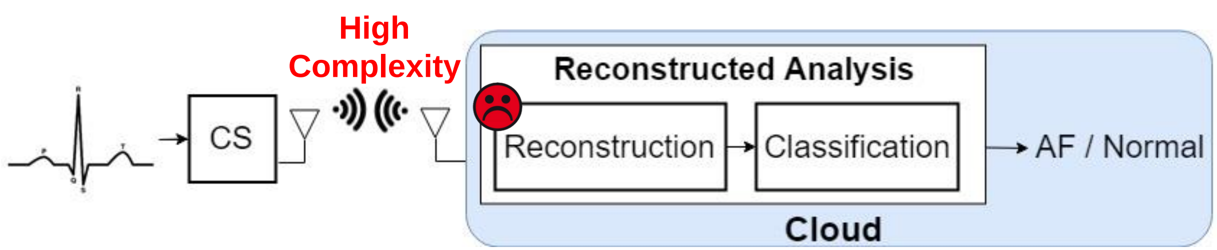
- Sensor
  - DWT-Based



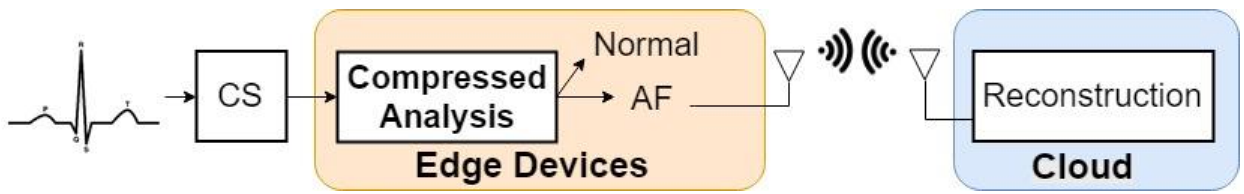
  - CS-Based



- Analysis
  - Reconstrcted (RA)



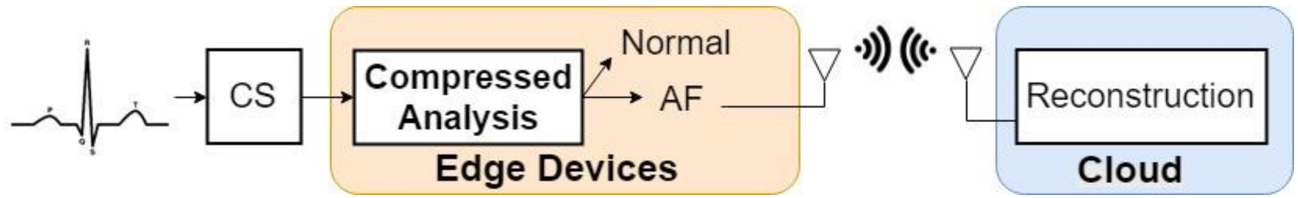
  - Compressed (CA)



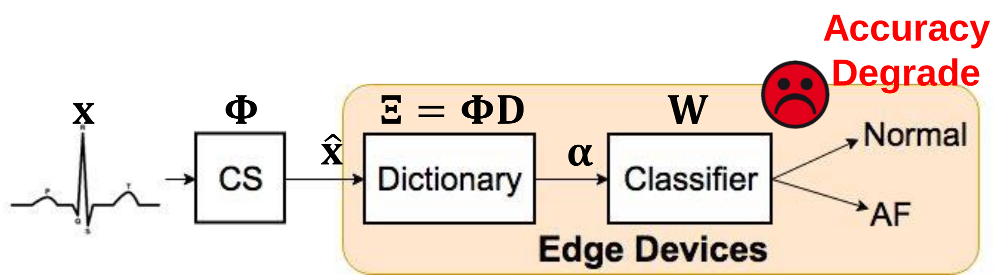
Scheme Development (2/2)

- Compressed Analysis

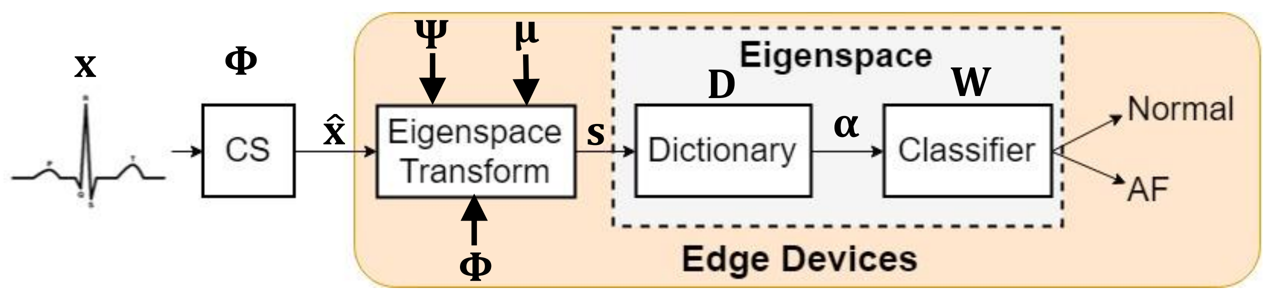
  - Prototype



  - Naïve

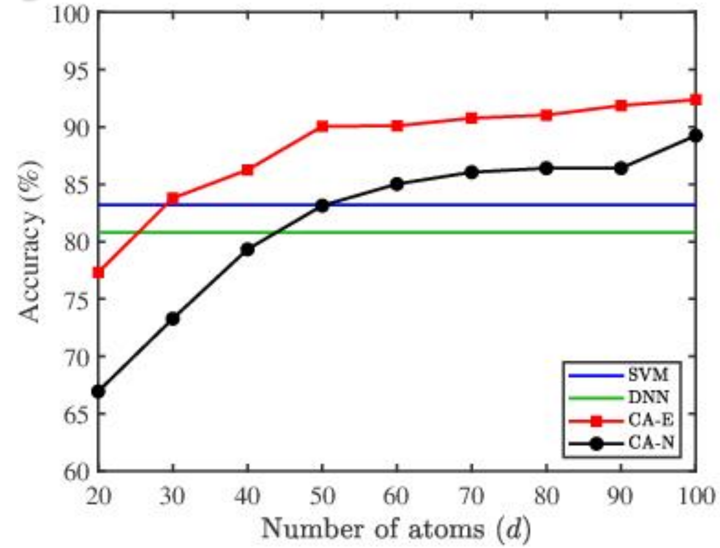


  - Eigenspace-aided



Simulation Results (1/3) Different Dictionary Size

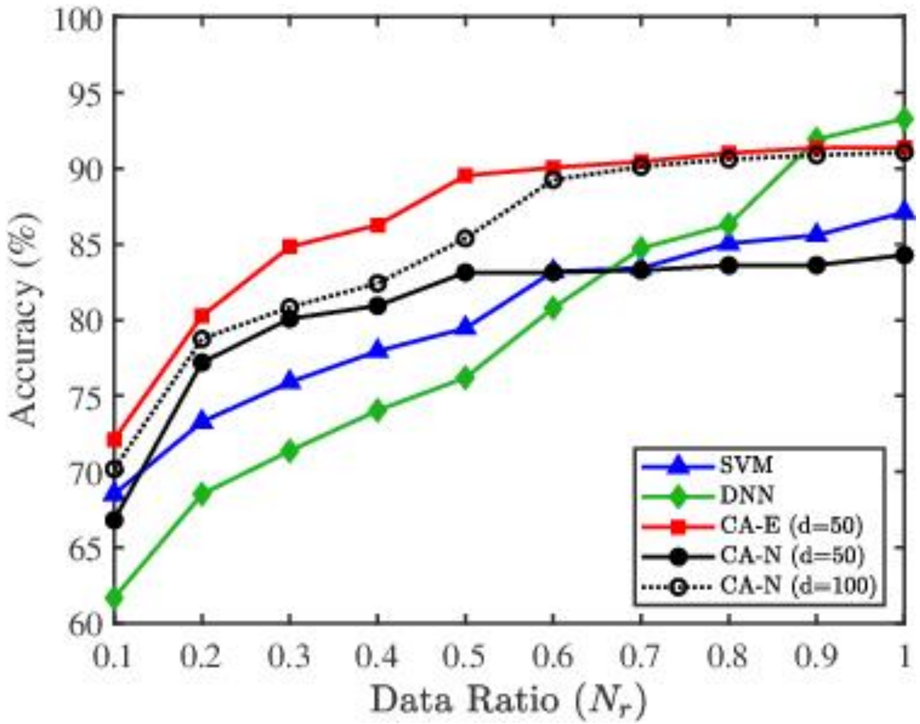
- Accuracy vs Dictionary Size
  - To surpass DNN & SVM (~85%), CA-E needs **30 atoms**, but CA-N needs 60 atoms.
  - Under same number of atoms, CA-E outperforms CA-N by about 7%.
- CA-E-50 *vs.* CA-N-100
  - Reduce about **67%** parameters (Memory↓)
  - Reduce about **87%** inference time (Power↓)
  - Reduce about **76%** training time (Power↓)



Model	# Parameters	Training Time (s)	Inference Time (ms)	Accuracy (%)
CA-N (100)	13k	452.56	26.94	89.24 $\pm$ 0.520
CA-E (50)	4.25k	107.15	3.50	90.05 $\pm$ 0.256

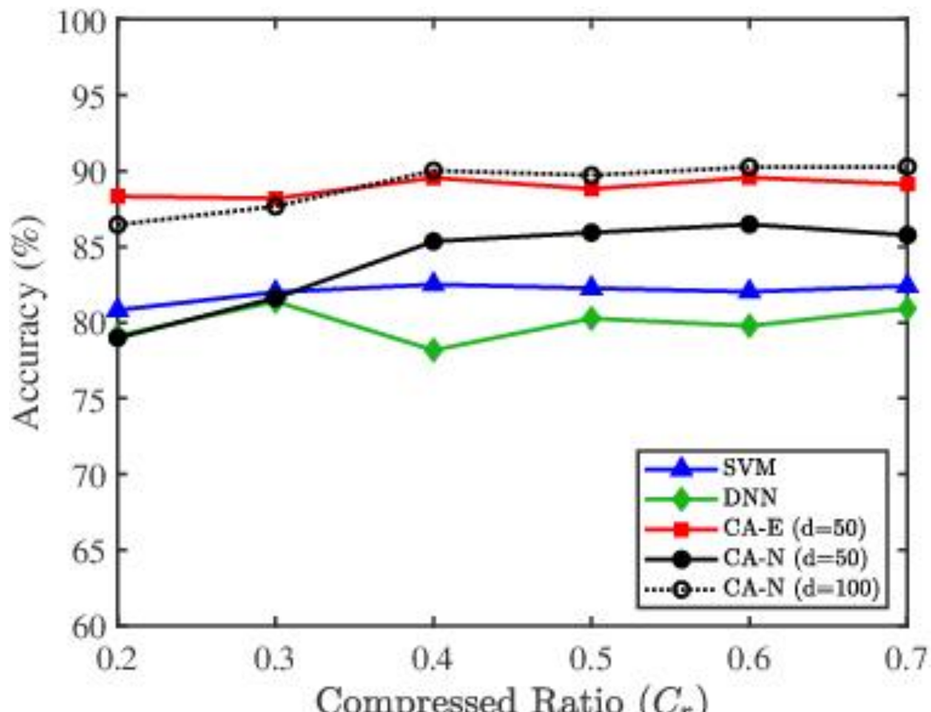
Simulation Results (2/3) Different Data Set Size

- CA-E is **more immune** to limited data challenge (ex. $N_r \leq 0.5$)
  - SVM and DNN dramatically drops below 80%
  - CA still maintain the performance
  - CA-E outperforms CA-N in **7% margin** when the number of atoms is the same.



Simulation Results (3/3) Different Compressed Ratio

- CA-E can achieve about 90% accuracy under all compressed ratios
  - CA-N requires 100 atoms to achieve same level of performance
  - SVM and DNN have only about 80%
- CA-E is robust and address the entailed problems of variation of compress ratio



Conclusion

- We propose an eigenspace-aided compressed analysis for ECG telemonitoring, using
  - PCA to mitigate the influence of sensing matrix and reduce the dimension
  - TDDL to learn predictive sparse coding at eigenspace.

- The proposed eigenspace-aided compressed analysis achieves
  - Low complexity
  - High generalization
  - High stability of different compressed ratios

Reference

[1] F. Touati and R. Tabish, “U-healthcare system: state-of-the-art review and challenges,” in *Journal of Medical Systems*, pp.120, May 2013.

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[3] M. Y. Tsai, C. Y. Chou and A. Y. Wu, “Robust compressed analysis using subspace-based dictionary for ECG telemonitoring systems,” in *Proc. IEEE Int. Workshop on Signal Process. Syst.*, Oct. 2017

[4] W. Shi, J. Cao, Q. Zhang, Y. Li, and L. Xu, “Edge Computing: Vision and Challenges,” in *IEEE Internet Things J.*, vol. 3, no. 5, pp. 637-646, Oct. 2016.

[5] J. Mairal, F. Bach and J. Ponce, "Task-driven dictionary learning," in *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 34, no. 4, pp. 791-804, April 2012.

[6] J. Mairal, F. Bach, J. Ponce, and G. Sapiro. “Online dictionary learning for sparse coding,“ ICML, 2009.

Thanks for your attention

Q&A

Backup

Experimental Setting

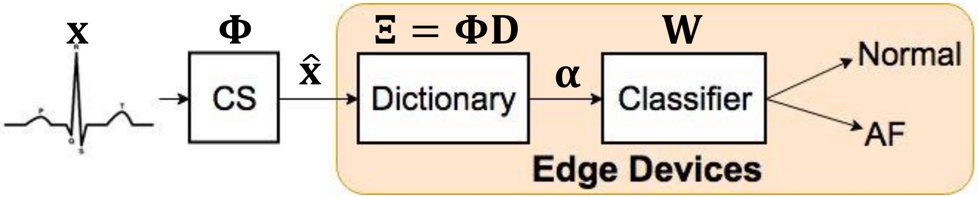
- ECG signals were recorded from the intensive care unit (ICU) of stroke in National Taiwan University Hospital (NTUH)
  - 231 normal records and 58 AF records (labeled by doctors)
  - Sample Frequency: 512 Hz
  - Each record randomly sample 2250 seconds
    - 1250 for training
    - 1000 for testing
- CS setting
  - Entries of sensing matrix: *Bernoulli (0.5)*
- Simulation Environment
  - Measured on Intel i5-4200M CPU @ 2.5 GHz
  - Using Python3

TABLE I: Parameters setting for learning models

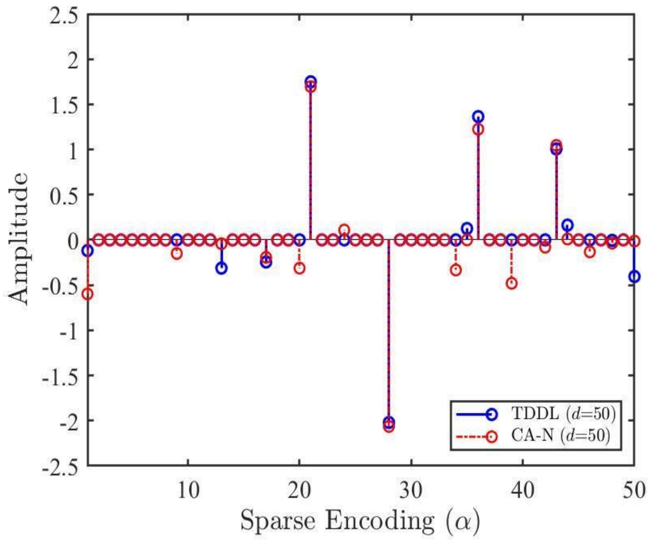
CA-E and CA-N	
ℓ_1-Constraint (λ_1)	[0.2, 0.5, 0.8]
Regularization (ν)	[10^{-5}, 10^{-4}]
SVM	
Kernel	Radial Basis Function
Gamma (γ)	[0.08, 0.10, 0.12, 0.15, 0.2]
Cost (C)	[500, 800, 1000]
DNN	
Hidden Layer Dimension	[(16,32), (32,64), (64,128), (128,256), (8,16,32), (16,32,64), (32,64,128)]

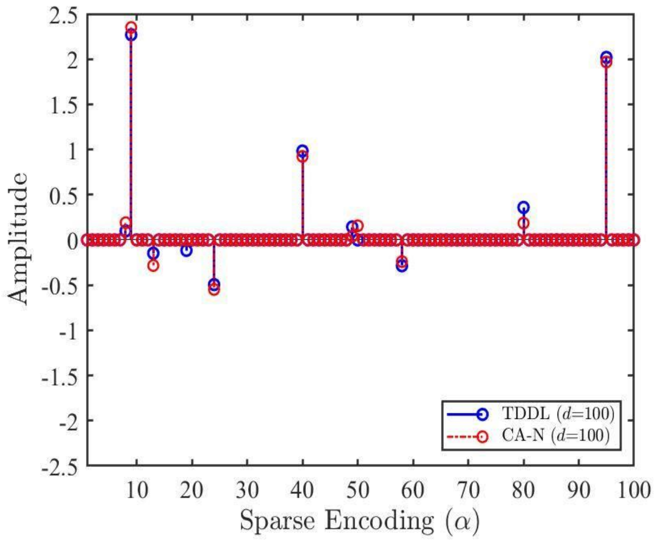
Analysis of CA-N

- We need to increase the number of atoms in dictionary to compensate the performance degrade



- Figures below also present the sparse codings in original domain as comparison group.





Comparison of CA-E and CA-N

- CA-E-50 *vs.* CA-N-100
  - Reduce about **67%** parameters
  - Reduce about **76%** training time,
  - Reduce about **87%** inference time
  - Smaller performance variance

Far smaller classifier with faster training and inference time

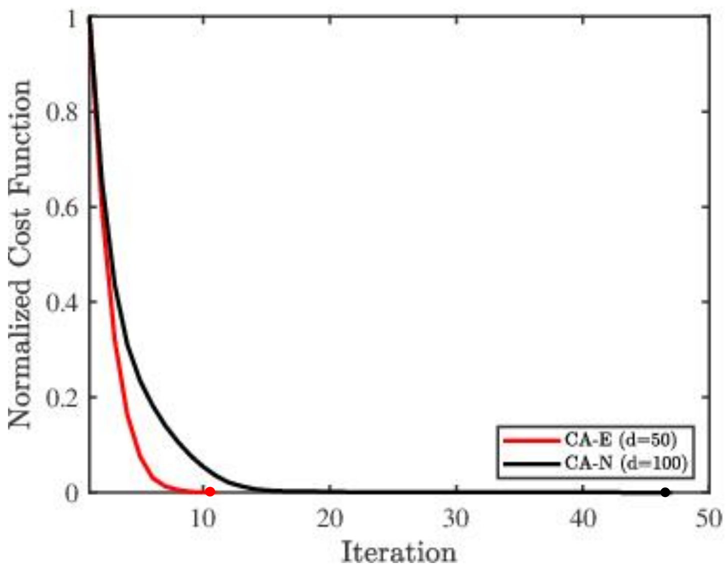
- The bottleneck of training and inference time lies in **FISTA**

Model	# Parameters	Training Time (s)		Inference Time (ms)				Accuracy (%)
		Total	FISTA	Total	FISTA	# Iter	1 Iter	
CA-N (d=100)	$M \times d + d \times N_c$ (13k)	452.56	306.33	26.94	26.94	35.5	0.759	89.24 $\pm$ 0.520
CA-E (d=50)	$r \times d + d \times N_c$ (4.25k)	107.15	61.59	3.50	3.49	15.2	0.229	90.05 $\pm$ 0.256

M = 128, r = 83 and N_r = 0.6

Detailed Timing Analysis

- The bottleneck in FISTA is $\nabla_\alpha f$ operation
  - $\nabla_\alpha f = \nabla_\alpha \frac{1}{2}\|\mathbf{x}-\mathbf{D}\boldsymbol{\alpha}\|_2^2 = \mathbf{D}^T\mathbf{D}\boldsymbol{\alpha} - \mathbf{D}^T\mathbf{x} \rightarrow O(d^2)$
  - Above order matches the following table
- CA-E accelerates FISTA by
  - **Cut off the complexity of each iteration**
  - **Reducing the number of iteration**



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Reference

[1] I. Daubechies, M. Defrise, and C. D. Mol, “An iterative thresholding algorithm for linear inverse problems with a sparsity constraint,” *Commun. Pure Appl. Math.*, vol. 57, pp. 1413–1457, 2004.

[2] A. Beck and M. Teboulle, “A fast iterative shrinkage-thresholding algorithm for linear inverse problems”, *SIAM Journal on Imaging Sciences*, vol. 2, pp. 183–202, 2009.