

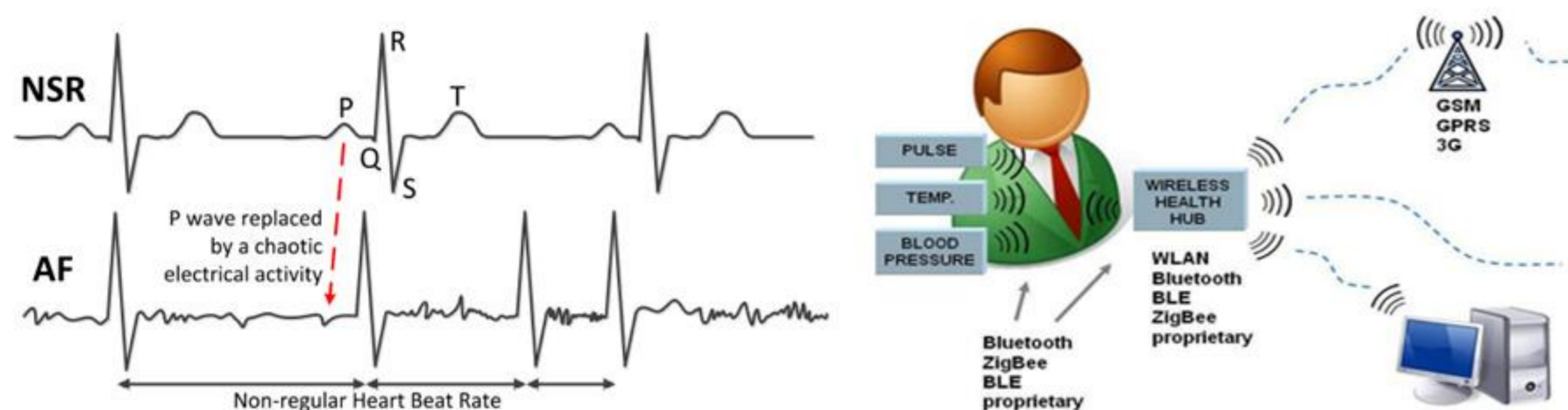
# Compressive Sensing Based ECG Monitoring with Effective AF Detection

Hung-Chi Kuo, Yu-Min Lin and An-Yeu (Andy) Wu  
email: charleykuo@access.ee.ntu.edu.tw



## Atrial Fibrillation & ECG Monitoring

- Atrial Fibrillation (AF) is the most common cardiac arrhythmia
  - Increases the risk of stroke by 5-fold [1]
  - Electrocardiography (ECG) is used in AF detection
  - ECG-based AF detection algorithms [5][6]
- Wireless ECG monitoring system is the key of home care for AF patients
  - Wireless Sensors → Hub → Cloud & Doctor

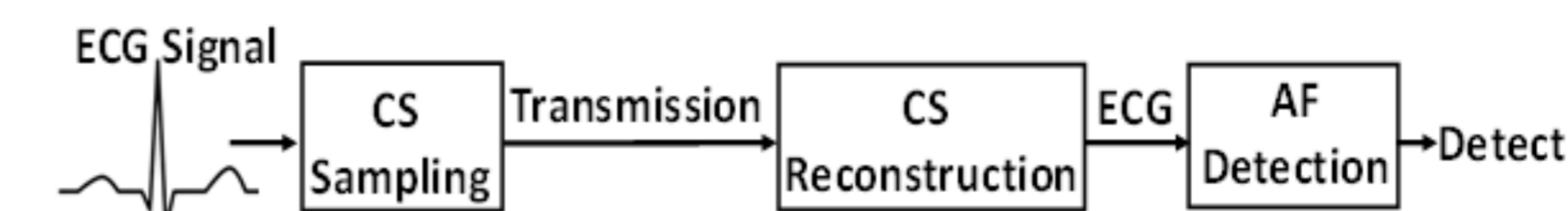


## Compressive Sensing for ECG Monitoring

- Traditional measured-and-compressed ECG monitoring suffer from high power consumption



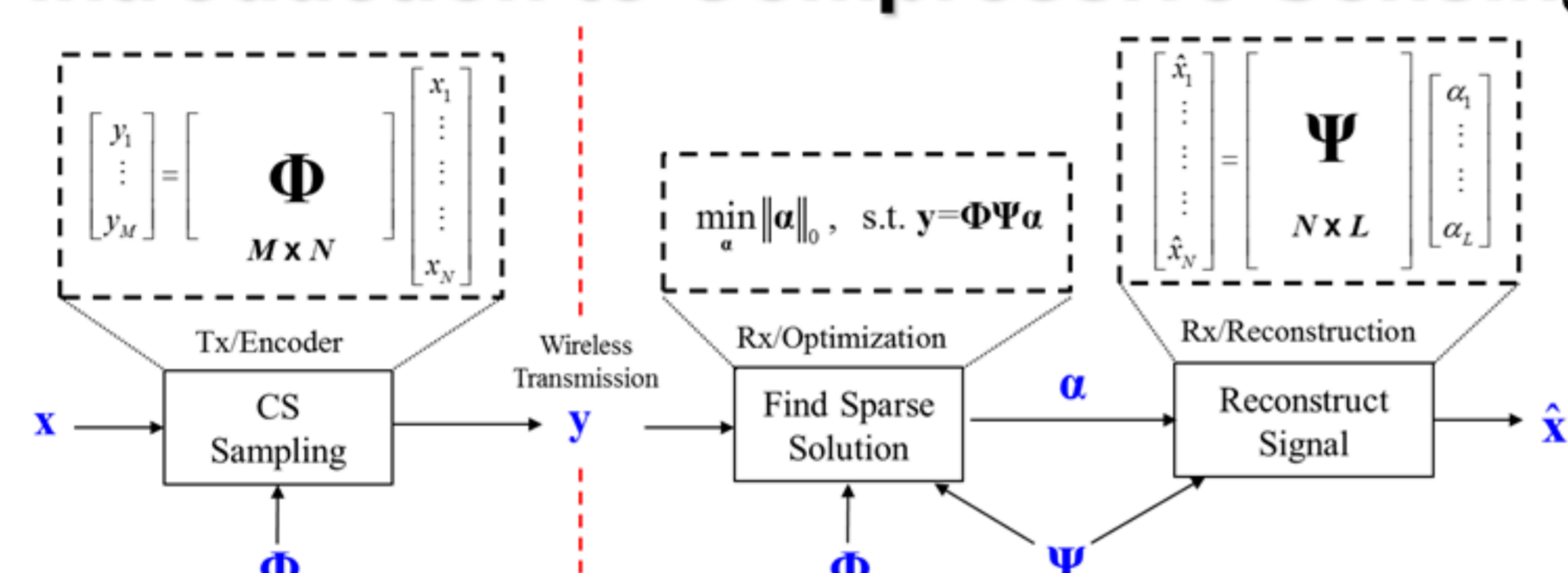
- Low-power compressive sensing (CS) based ECG monitoring system [4] for AF detection



- Proposed CS-based ECG monitoring system with built-in AF detection



## Introduction to Compressive Sensing

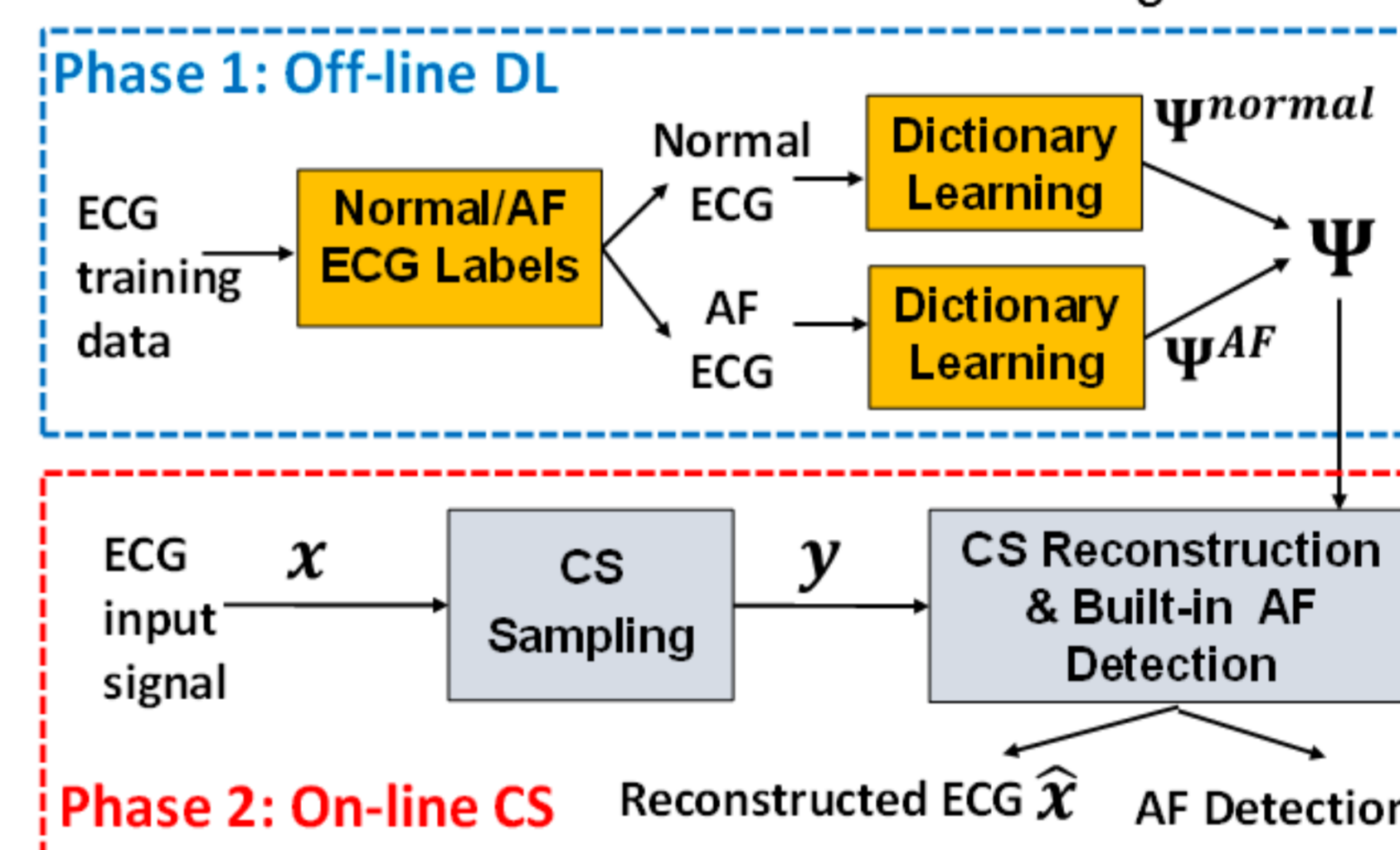


- Sensor: Random sampling N-dim  $x$  by sensing matrix  $\Phi \rightarrow M$ -dim  $y$  ( $M < N$ )
- Receiver: Reconstruct signal  $x$  from measurement  $y$ 
  - $l^1$ -Minimization: Basis Pursuit (BP) [8], Orthogonal Matching Pursuit (OMP)
  - $x$  needs to be sparse in specific sparsifying basis  $\Psi$ ,  $x_{N \times 1} = \Psi_{N \times P} \alpha_{P \times 1}$
  - State-of-the-art takes Discrete Wavelet Transform (DWT) as sparsifying basis [4]
  - ECG on DWT is not sparse enough  $\rightarrow K \uparrow \rightarrow M > O(K \cdot \log(N/K))$  [2]  $\rightarrow M \uparrow$
  - Low compression ratio and bad energy efficiency



## Proposed CS-based ECG Monitoring System with Built-in AF Detection

- Phase 1: Separate training data into AF and normal ECG waveform. Applied dictionary learning to generate  $\Psi_{N \times 2P} = [\Psi_{N \times P}^{Normal} \Psi_{N \times P}^{AF}]$
- Phase 2: AF detection in CS reconstruction stage



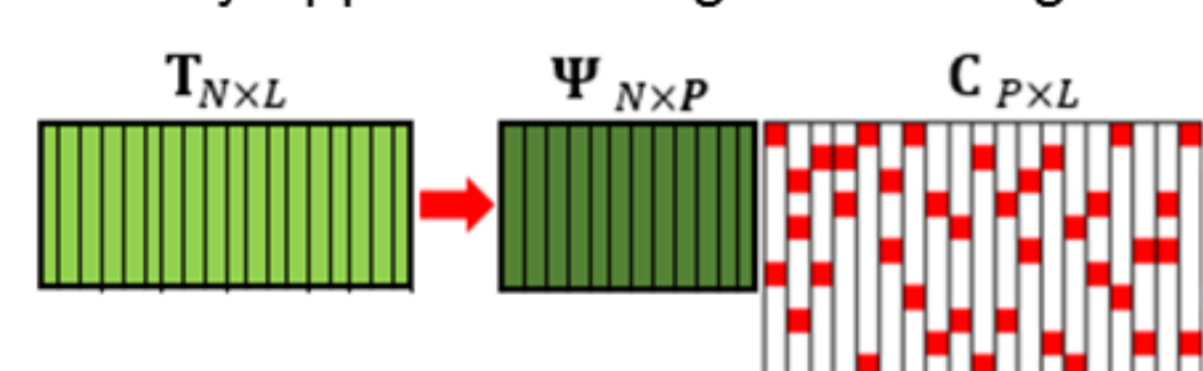
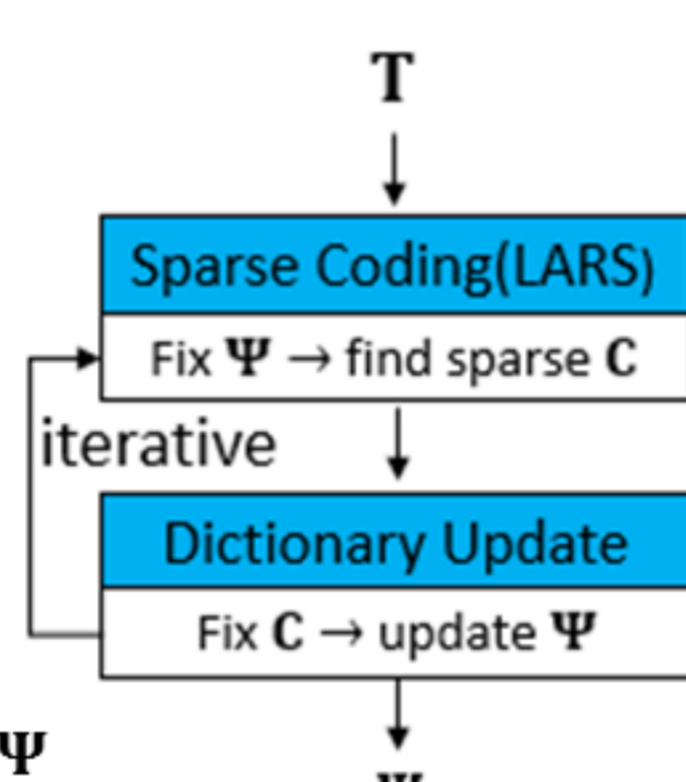
## Dictionary Learning [7]

- Training data  $T$  can be represented by linear combination of dictionary  $\Psi$  with sparse coefficients  $C$

$$\text{Solve } \min_{\Psi, C} \frac{1}{L} \sum_{i=1}^L \left( \frac{1}{2} \|t_i - \Psi c_i\|_2^2 + \lambda \|c_i\|_1 \right)$$

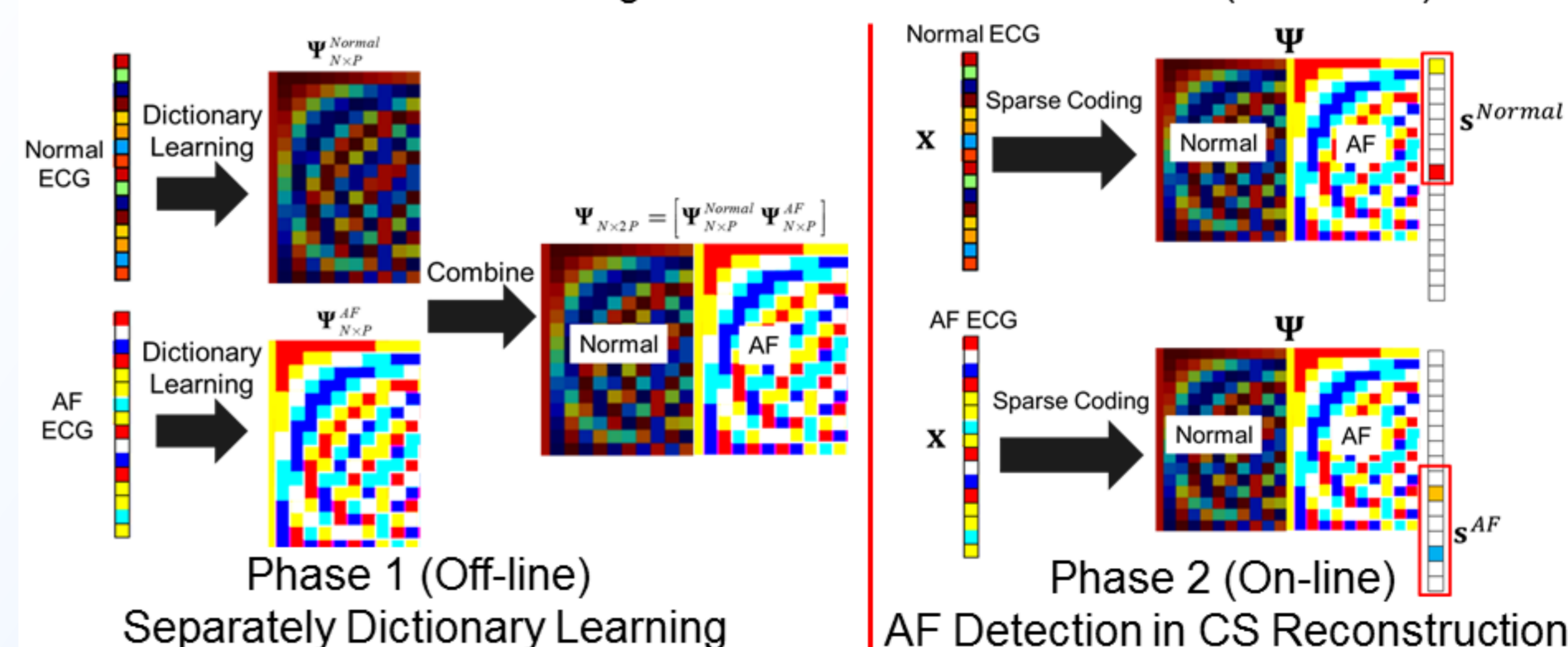
- Two stage procedure

- Sparse coding
  - Basis Pursuit Denoising (BPDN)
- Dictionary update
  - Online updating
- Iteratively applies two stages on  $T$  to generate  $\Psi$



## Built-in AF Detection in CS Reconstruction

- Sparse Representation Classifier (SRC) in face recognition
  - Test sample as a sparse linear combination of trained dictionary
  - Sparse solution via  $l^1$ -Minimization
- CS reconstruction using  $l^1$ -Minimization  $\rightarrow$  Detect AF (Classifier)

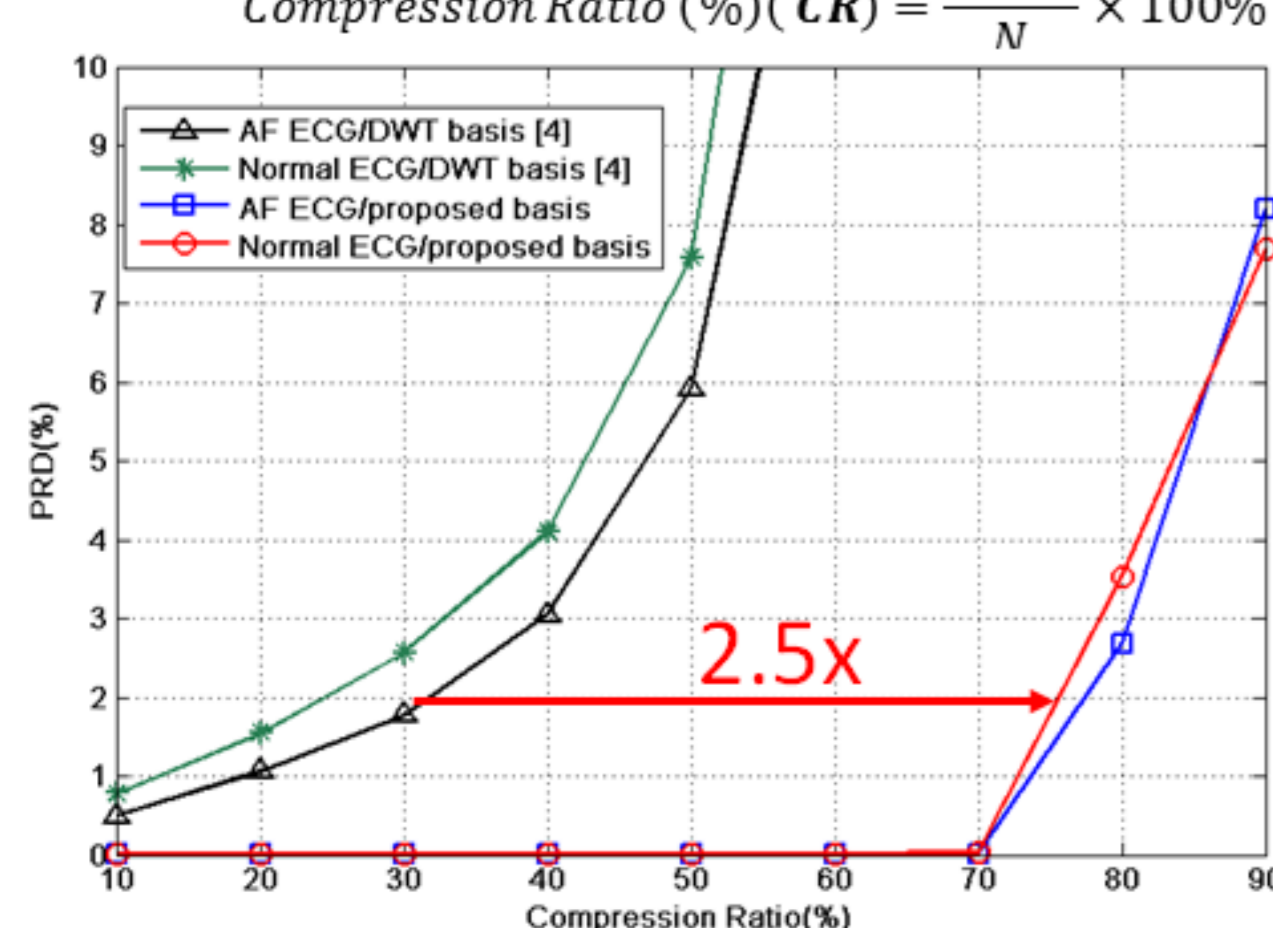


## Reconstruction Performance of CS-based ECG Compression with Different Spasifying Basis

- Compare the proposed trained personalized basis with common predefined basis DWT [4]

$$\text{Percentage Root mean square Distance (PRD)} = \frac{\|x - \hat{x}\|_2}{\|x\|_2} \times 100\% \text{ [11]}$$

$$\text{Compression Ratio (CR)} = \frac{N - M}{N} \times 100\%$$



Parameter Settings	
Input Data Type	ECG from MIT-BIH Long-Term AF Database (LTAfDB) [10]
Sampling Frequency	256 Hz
# of Training Vectors (L)	2500
Input Dimension (N)	256
# of Dictionary Atoms (P)	512
Sampling Matrix	Random Gaussian Matrix
Trials	1000



## Performance of Built-in AF Detection

- A paroxysmal AF patient in MIT-BIH Long-Term AF who has both normal ECG and AF ECG

$$\text{Sensitivity} = \frac{\# \text{ of AF segments detected as AF}}{\text{Total AF segments (labels in database)}}$$

$$\text{Specificity} = \frac{\# \text{ of Normal segments detected as Normal}}{\text{Total Normal segments (labels in database)}}$$

$$\text{Detect}(s^{normal}, s^{AF}) = \begin{cases} \text{AF ECG,} & \text{if } \|s^{AF}\|_2 \geq \|s^{normal}\|_2 \\ \text{Normal ECG,} & \text{if } \|s^{AF}\|_2 < \|s^{normal}\|_2 \end{cases}$$

	70%	80%	90%
CR	70%	80%	90%
Sensitivity	85.4%	92.4%	96.0%
Specificity	85.6%	86.0%	97.2%