Compressive Sensing Based Indoor Human Positioning Using A Single Thermopile Point Detector

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Outlines

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- System Overview
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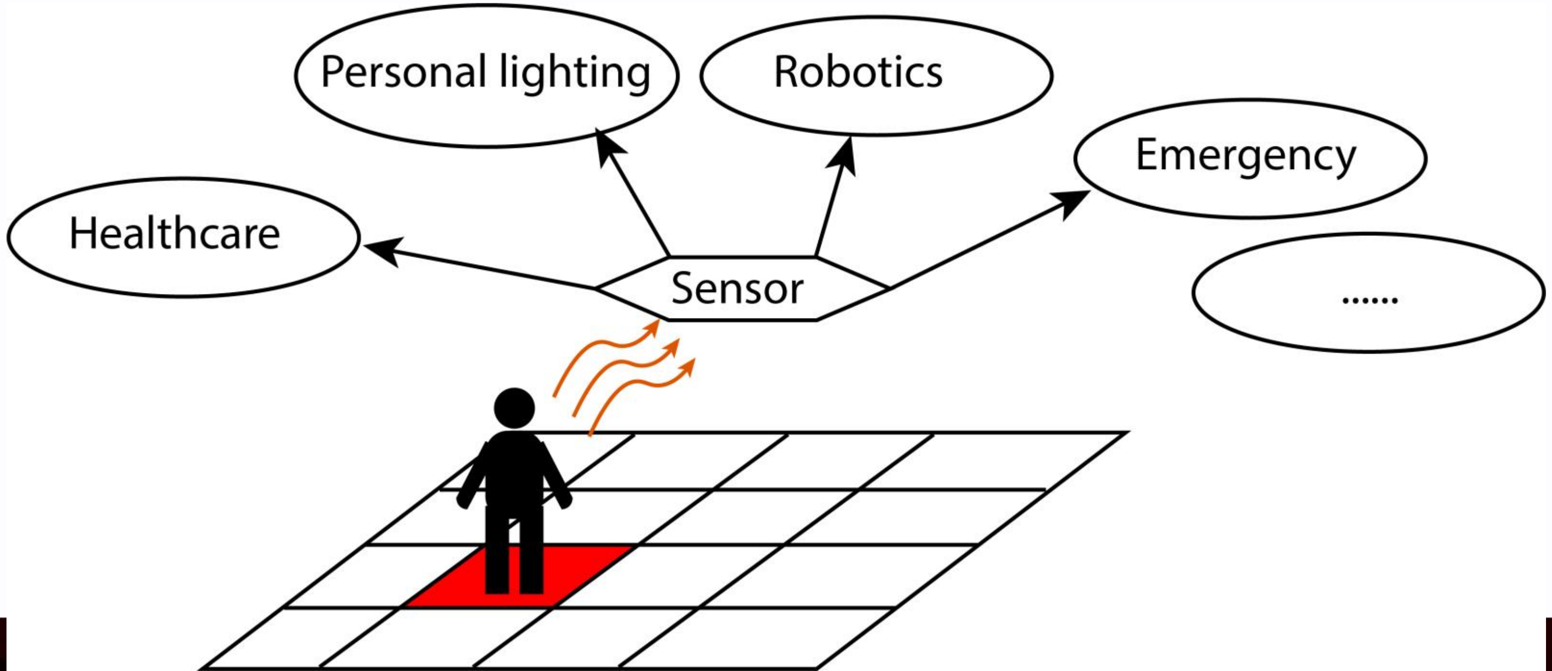
Background

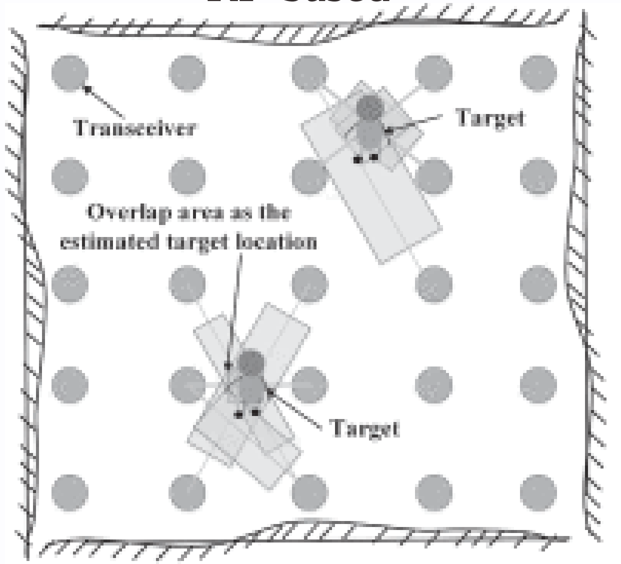
- Indoor positioning has become very popular in recent years.
- Real world applications are many:
  - Healthcare, personal lighting, heating/cooling, robotics, emergency response system, etc.



Background-cont.

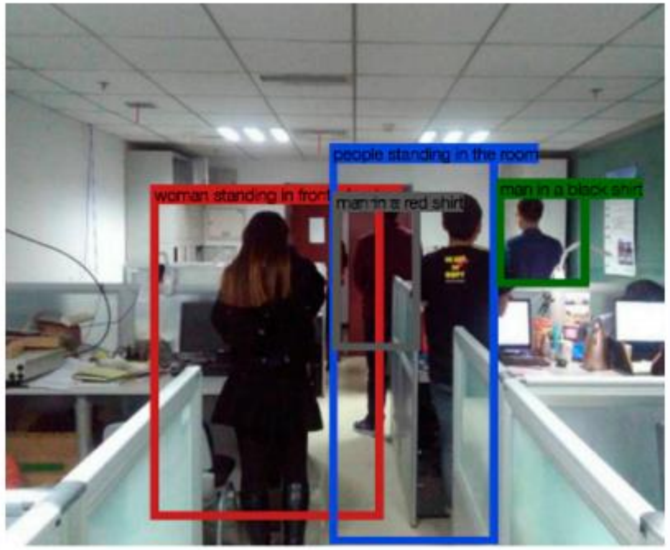
- Typical technologies can be categorized into
  - RF based: multiple sensors, large deployment effort.
  - Image-based: privacy issue.
  - IR sensor-based: high cost, limited FOV.

RF-based



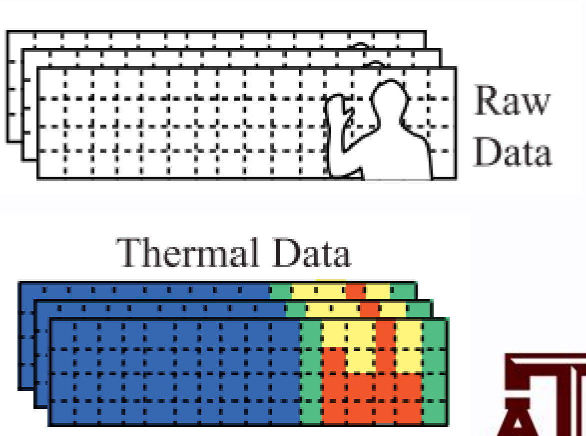
[Wang, Ju, et al., TMC, 2016]

Camera-based



[Jiao, Jichao, et al., *Sensors*, 2017]

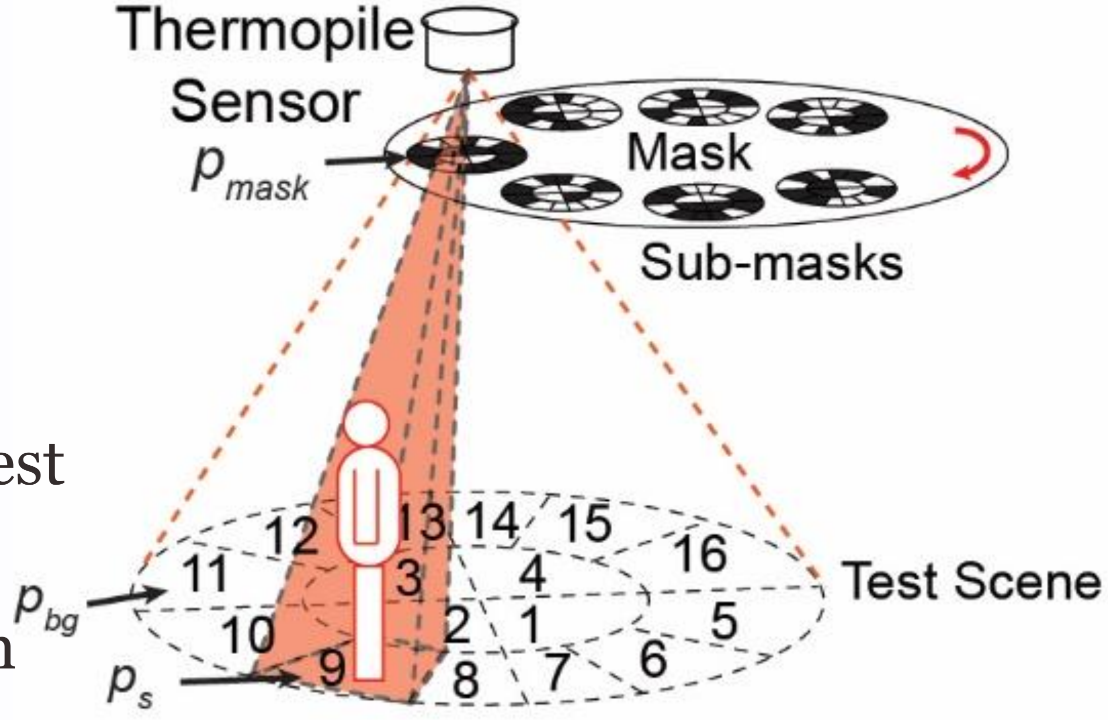
IR sensor-based



[Tyndall, Ash, et al., *IEEE Sensors*, 2016]

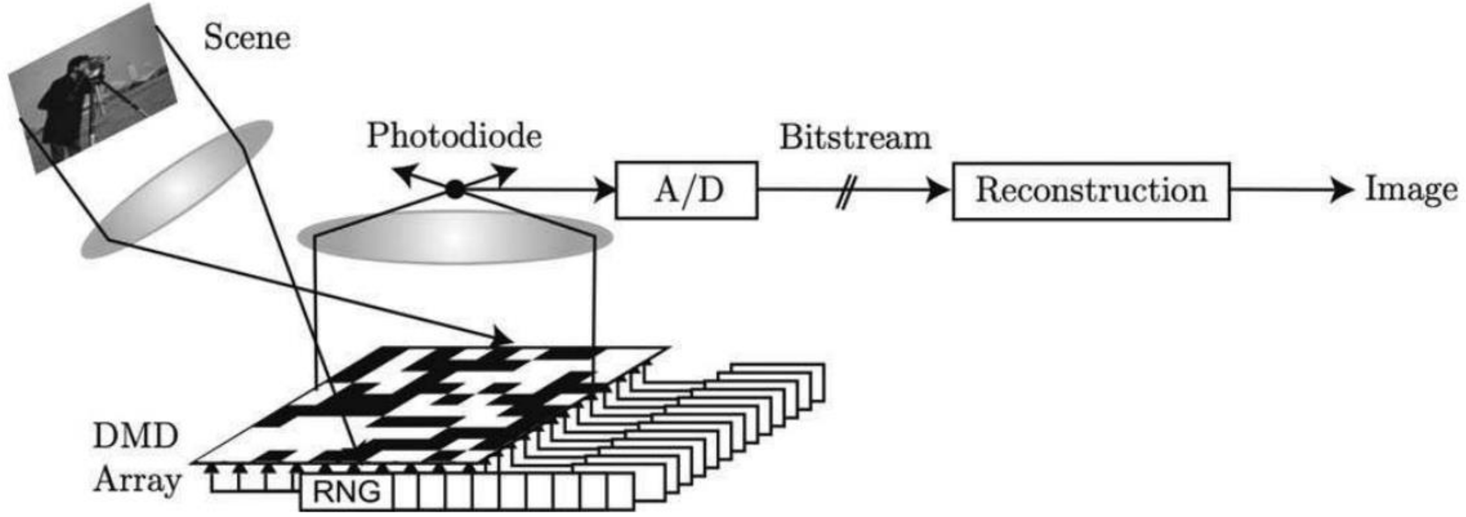
System Overview

- We propose a solution that uses one point detector to do the indoor positioning.
- Thermopile detector is on the ceiling.
- A binary coded mask.
- Each sub-mask fills the FOV of the sensor.
- The projection of each sub-mask segments test scene into multiple zones.
- The sensor generates a series of signals when the mask rotates.

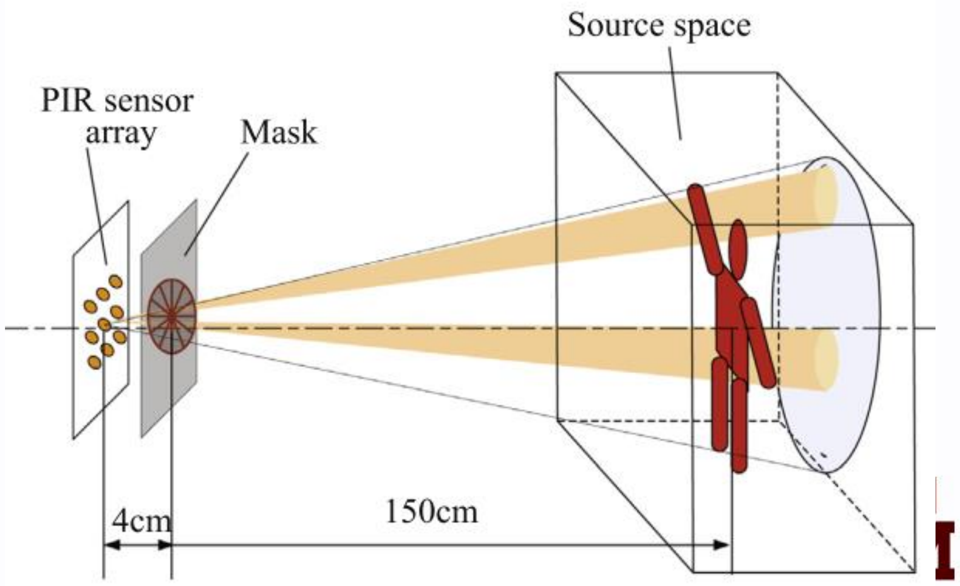


Introduction to Compressive Sensing

- Conventional sampling theory requires a sampling rate > 2 times of Nyquist rate to ensure an accurate reconstruction.
- CS theory recovers the original signal with very few measurements.
- Some examples: single pixel camera, human activity recognition, …



[M. F. Duarte et al., SPM, 2008]



[Q. Guan, et al., 2014]

Introduction to Compressive Sensing

- Consider a vector $\boldsymbol{x} \in \boldsymbol{R}^{N\times 1}$, a basis matrix $\boldsymbol{\Psi} = [\boldsymbol{\psi}_1, \boldsymbol{\psi}_2, \dots, \boldsymbol{\psi}_N]$, a weight vector $\boldsymbol{s} \in \boldsymbol{R}^{N\times 1}$. Then $\boldsymbol{x}$ can be represented as

$$\boldsymbol{x} = \boldsymbol{\Psi}\boldsymbol{s} = \sum_{i=0}^{N} s_i \boldsymbol{\psi}_i$$

- Define the vector $\boldsymbol{x}$ is "k-sparse" if only k of the s_i are nonzero.
- If $k \ll N$, CS theory can reconstruct $\boldsymbol{x}$ if using only a small number of measurements.

Introduction to Compressive Sensing

- We consider a linear measurement that can be written as:

$$\boldsymbol{y} = \Phi \boldsymbol{x} + \boldsymbol{n} = \Phi \Psi \boldsymbol{s} + \boldsymbol{n} = A\boldsymbol{s} + \boldsymbol{e}$$

- $\Phi, A \in \boldsymbol{R}^{M \times N}$ and $M < N$. $\boldsymbol{y}, \boldsymbol{e} \in \boldsymbol{R}^{N \times 1}$, and $\boldsymbol{e}$ is the noise vector.
- If A satisfies the Restricted Isometry Property (RIP), $\boldsymbol{s}$ can be reconstructed from the l_1-minimazition with relaxed constraints:

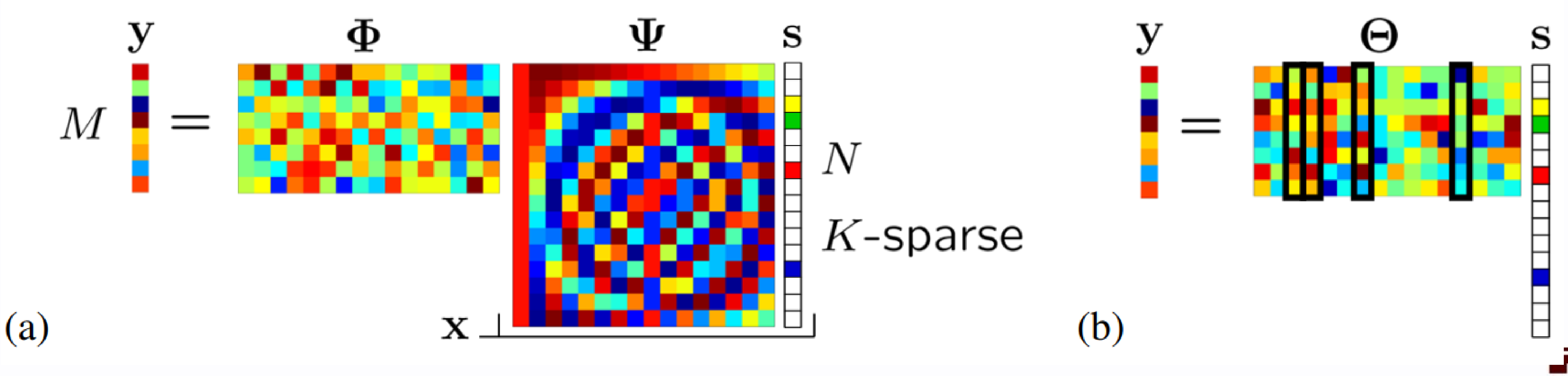
$$\hat{\boldsymbol{s}} = \arg\min_{\boldsymbol{s}} \|\boldsymbol{s}\|_1 \ \text{subject to} \ \|A\boldsymbol{s} - \boldsymbol{y}\|_2 < \epsilon$$

- ϵ is the bound of the noise, and $\|\cdot\|_1$ and $\|\cdot\|_2$ denote the l_1 and l_2 norm.

[E. Candes, T. Tao, *IEEE Trans. Inform. Theory*, 2005]

Introduction to Compressive Sensing

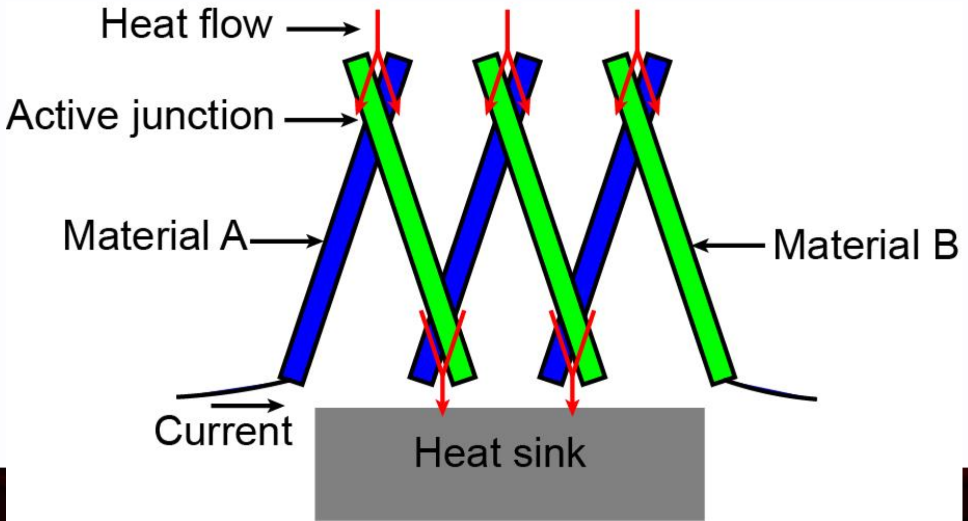
- CS could reconstruct sparse signals with a much lower number of measurements.
- The minimum number of measurements $M \geq O(k \ln(\frac{N}{k}))$.



[R. G. Baraniuk, *IEEE Signal. Process. Mag.*, 2007]

Introduction to Thermopile Detector

- Thermopile detector is based on Seebeck effect.
- If there is a temperature difference between the two junctions of the thermocouple junction pair, a voltage is produced.
- A thermopile point detector consists of n junction pairs that are connected in series.



Introduction to Thermopile Detector

- The responsivity is $\Delta V = nS\Delta T$, where S is the relative Seebeck coefficient.
- The heat transfer function can be written as

$$C\frac{d\Delta T}{dt} + K\Delta T = P_e$$

- The output voltage is

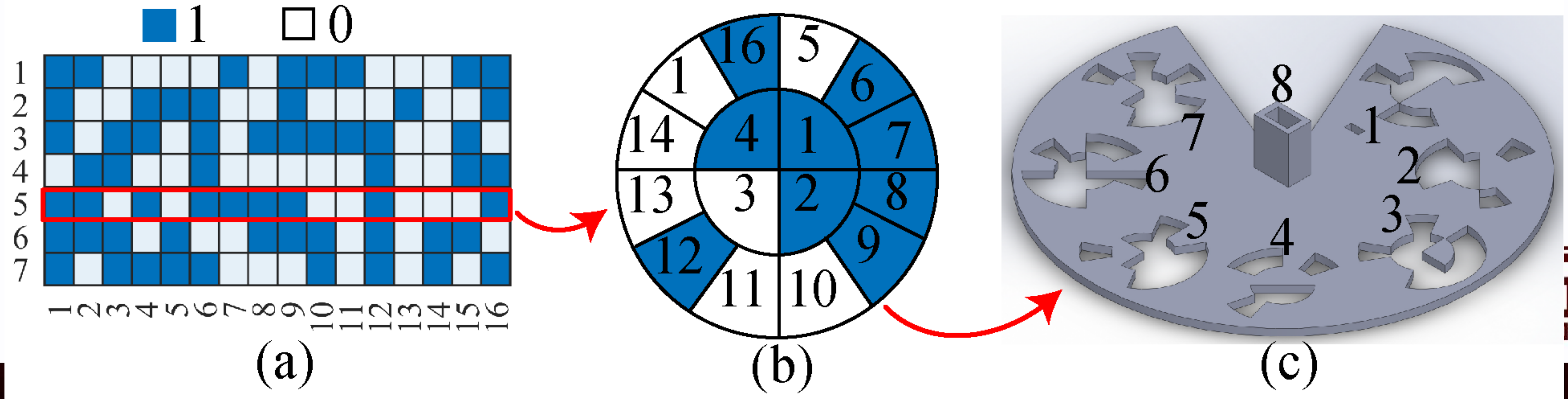
$$\Delta V = nS\Delta T = \frac{nSP_e\left(1 - \exp\left(-\frac{t}{\tau}\right)\right)}{K}$$

- When time $t > 3\tau$, ΔV is proportional to P_e.

ΔT: temperature difference
P_e: infrared radiant energy
C: heat capacity
K: thermal conductance

Coded Mask Design

- One $M \times N$ binary matrix A is designed in Bernoulli distribution.
- In this study, M=7, and N=16.
- Each sub-mask is following the pattern of the row vector.
- The zone of the sub-mask is transparent if the entry of the vector is 0 and is opaque if the entry is 1.
- The actual mask consists of 8 sub-masks. And 1 of them is all transparent.

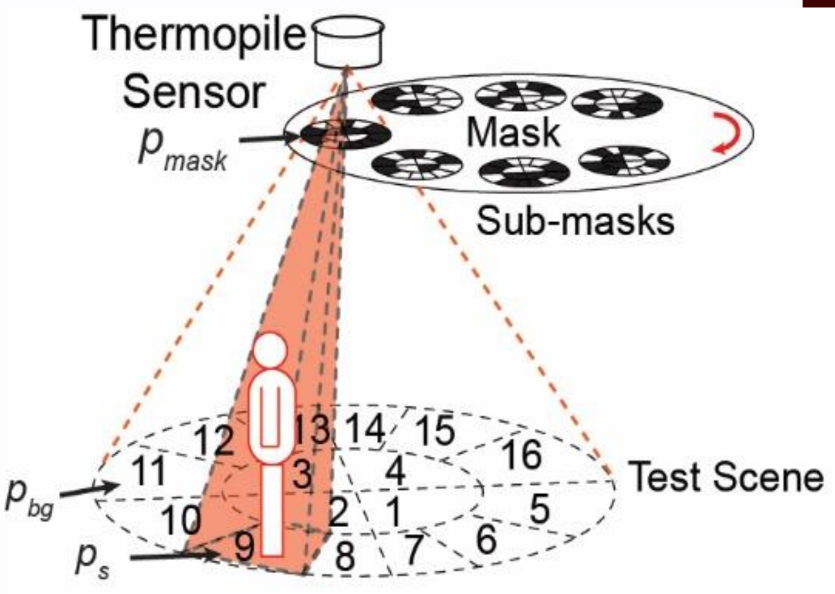


Problem Formation

- Infrared radiation energy of each zone is p_{bg} and p_s
- When the *i*-th sub-mask is in the FOV, the human is in the *j-th* zone, received infrared radiation of the thermopile sensor $y_{i,j}$ becomes

$$y_{i,j} = A_i \boldsymbol{x}_j + (\mathbf{1}_{1\times N} - A_i)\boldsymbol{x}_{mask} + \boldsymbol{n}$$

  - A_i : *i*-th row of the measurement matrix.
  - $\boldsymbol{x}_j$: a vector indicates the radiation of the test scene.
  - $\boldsymbol{x}_{mask}$: a vector indicates the radiation of the mask.
  - $\boldsymbol{n}$: noise.



$$\boldsymbol{x}_j = \{p_{bg}, p_{bg}, \dots, p_s, \dots p_{bg}\}$$

Problem Formation

- After all sub-masks are rotated once, stacking all M measurements

$$\boldsymbol{y} = A(\boldsymbol{x}_j - \boldsymbol{x}_{mask}) + \mathbf{1}_{1\times N}\boldsymbol{x}_{mask} + \boldsymbol{n}$$

- Define matrix $B = 2A - \mathbf{1}_{M\times N}$. Matrix B **satisfies RIP**.
- Substitute matrix A leads to

$$2\boldsymbol{y} = B(\boldsymbol{x}_j - \boldsymbol{x}_{mask}) + 1_{M\times N}\boldsymbol{x}_j + 1_{M\times N}\boldsymbol{x}_{mask} + 2\boldsymbol{n}$$

- When there is no human in the test scene,

$$2\boldsymbol{y}_{env} = B(\boldsymbol{x}_{bg} - \boldsymbol{x}_{mask}) + 1_{M\times N}\boldsymbol{x}_{bg} + 1_{M\times N}\boldsymbol{x}_{mask} + 2\boldsymbol{n}_{env}$$

- The difference can be written as

$$2\boldsymbol{y} - 2\boldsymbol{y}_{env} - 1_{M\times N}\boldsymbol{x}_j + 1_{M\times N}\boldsymbol{x}_{bg} = B(\boldsymbol{x}_j - \boldsymbol{x}_{bg}) + 2(\boldsymbol{n} - \boldsymbol{n}_{env})$$

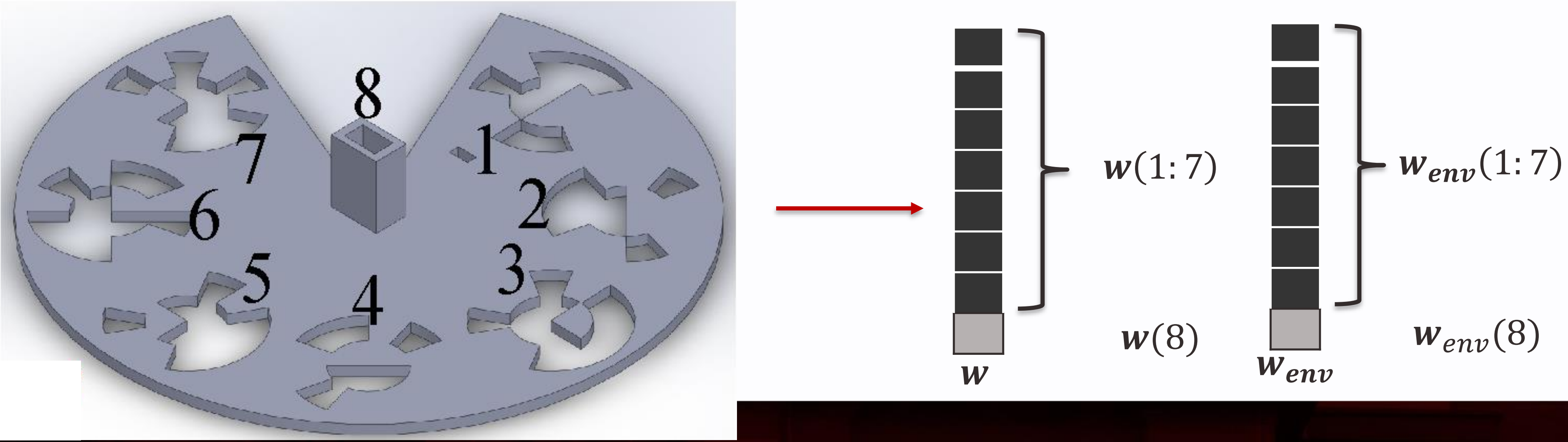
[G. Zhang, S. Jiao, X. Xu, L. Wang, *IEEE Int. Conf. Inf. Automat.*, 2010]

Problem Formation

$$2\boldsymbol{y} - 2\boldsymbol{y}_{env} - 1_{M\times N}\boldsymbol{x}_j + 1_{M\times N}\boldsymbol{x}_{bg} = B(\boldsymbol{x}_j - \boldsymbol{x}_{bg}) + 2(\boldsymbol{n} - \boldsymbol{n}_{env})$$

- In practice, after one period of rotation, there will be 8 kinds of values collected from the sensor, vector $\boldsymbol{w}$ and $\boldsymbol{w}_{env}$, for occupied and unoccupied situations.
- Denote the left side to be $\boldsymbol{f}$, which is equal to

$$2\boldsymbol{w}(1:7) - 2\boldsymbol{w}_{env}(1:7) - \boldsymbol{w}(8) + \boldsymbol{w}_{env}(8)$$



Problem Formation

- Eq. (6) becomes

$$\boldsymbol{f} = B(\boldsymbol{x}_j - \boldsymbol{x}_{bg}) + 2(\boldsymbol{n} - \boldsymbol{n}_{env}) = B\boldsymbol{x} + 2\tilde{\boldsymbol{n}}$$

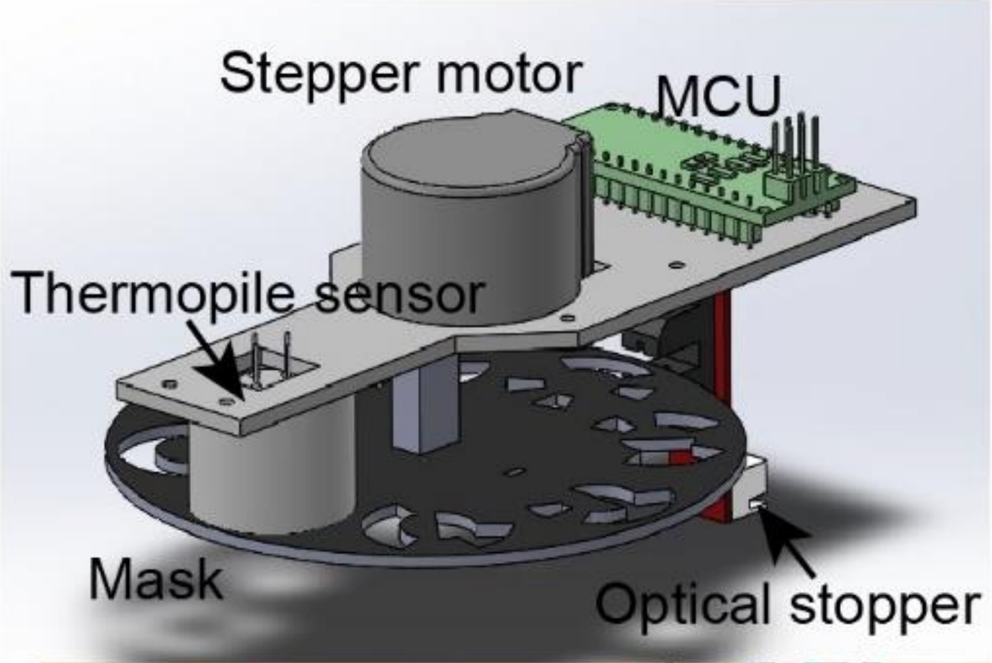
which has the same form of CS theory $\boldsymbol{y} = A\boldsymbol{s} + \boldsymbol{e}$.

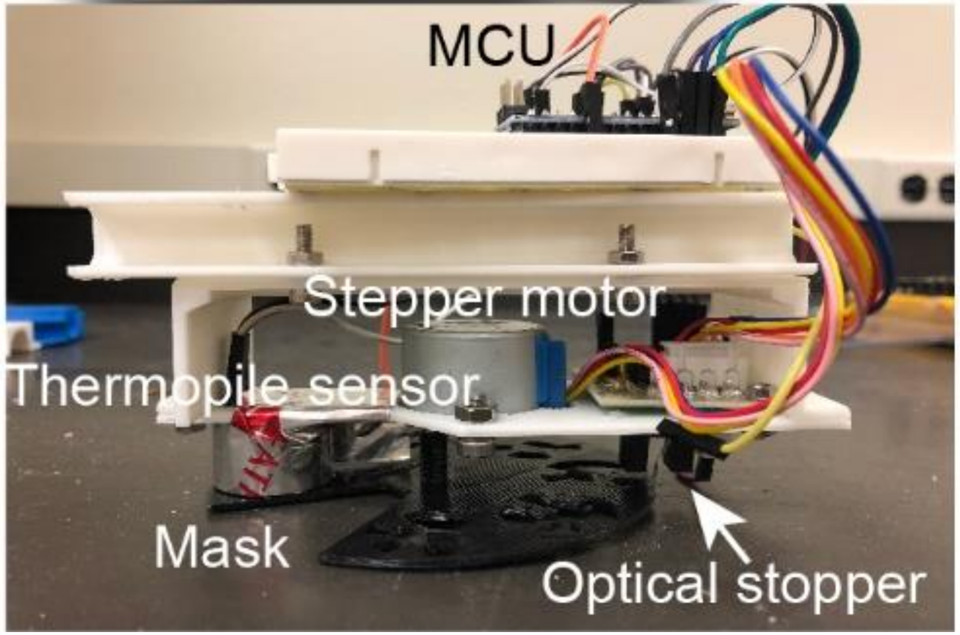
- $\boldsymbol{x}_j - \boldsymbol{x}_{bg} = \{0,0,\ldots,p_s,\ldots 0\}$, is 1-sparse vector.
- Matrix B satisfies RIP property.
- Thus, $\boldsymbol{x} = \boldsymbol{x}_j - \boldsymbol{x}_{bg}$ can be reconstructed via CS theory.
- Location L of the human target is the index of largest value:

$$L = \arg\max_i x(i)\text{, where } i = 1,2,\ldots,16 \quad (7)$$

System Design

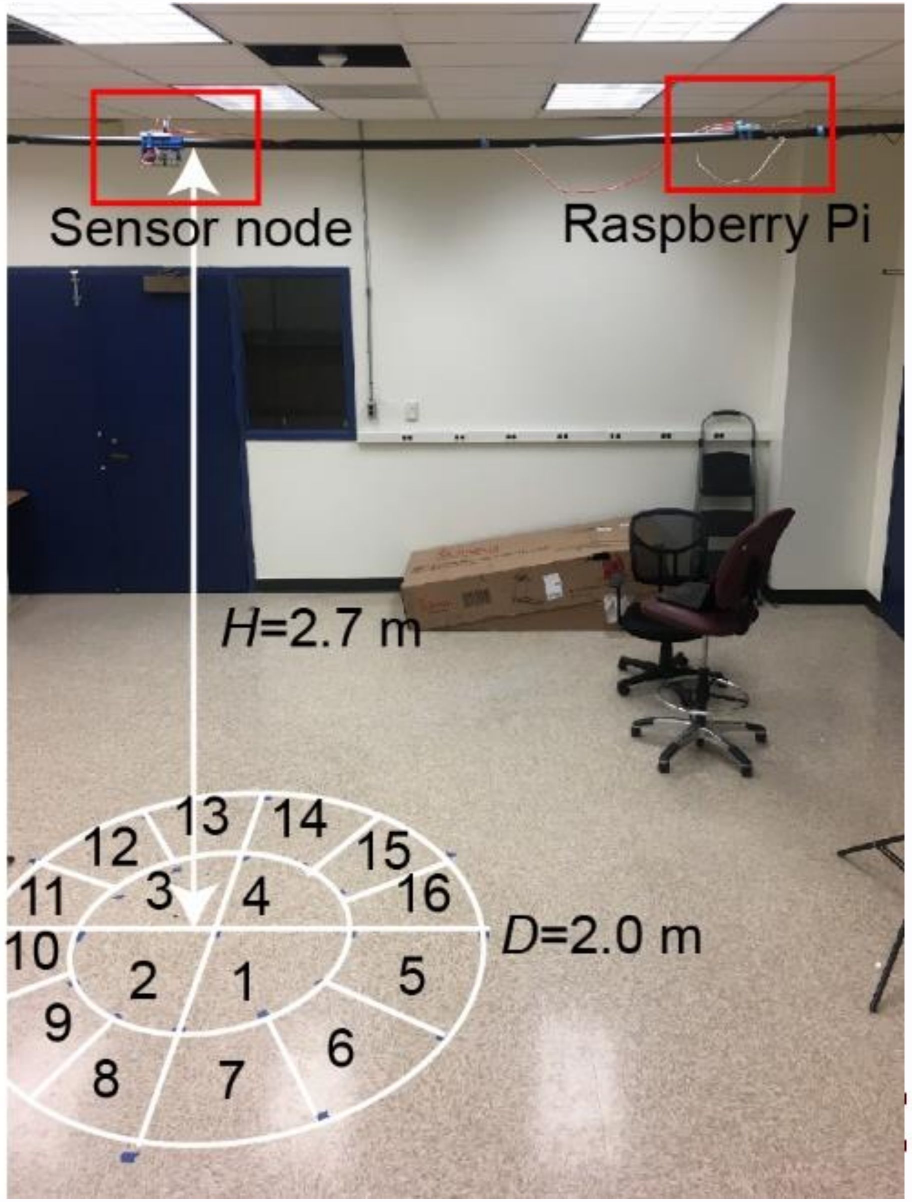
- The mask is driven by a stepper motor which is controlled by the Arduino Nano microcontroller.
- The optical stopper provides feedback
- Thermopile sensor is MLX90614, which returns the object temperature T_o and ambient temperature T_a.
- The received infrared radiation $P \propto (T_o^4 - T_a^4)$





Test Setup

- The sensor node is at height $H = 2.7$ m.
- The test scene is circular area with a diameter of 2 m and is segmented into 16 zones.
- MCU collects 10 pairs of temperature data (T_o, T_a) for each sub-mask.
- The unoccupied signals are collected firstly.
- Then, the human target stands at different zones.
- In each case, 4 periods of signals are collected.
- In total, 64 sets of data are collected.



Results

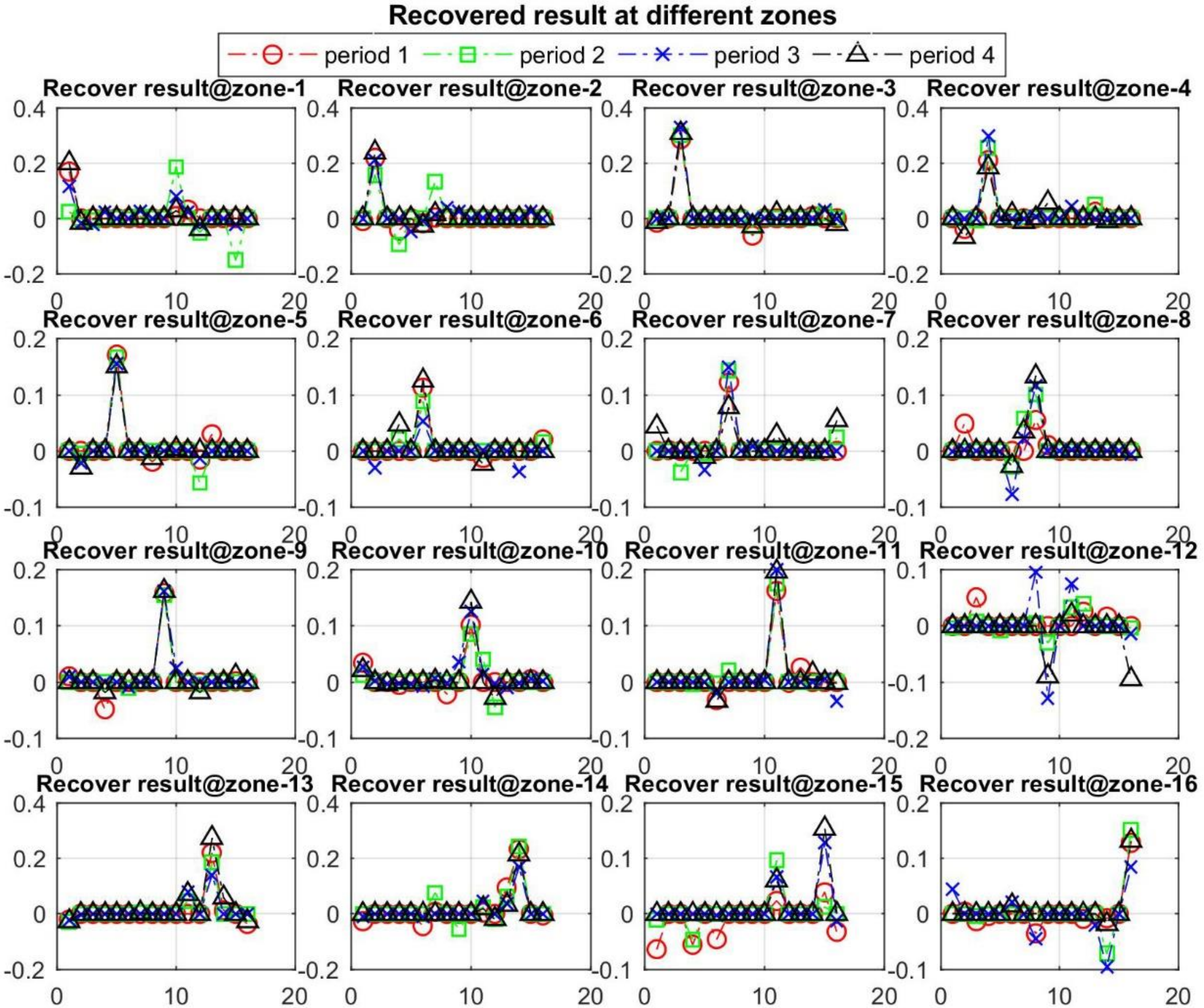
- In each period of rotating, 8 kinds of values are collected for each sub-mask. 10 samples data for each kind of value.
- Computing the average value then run the recovery algorithm and obtain the 8-length vector for each period.
- In this study, we choose Basis Pursuit Denoising (BPDN) algorithm to recovery with the optimization problem

$$\hat{\boldsymbol{x}} = \arg\min_{\boldsymbol{x}} ||\boldsymbol{x}||_1 \text{ subject to } ||B\boldsymbol{x} - \boldsymbol{f}||_2 < \epsilon$$

[S. Chen, et al.. *SIAM rev.*, 2001]

Results

- The predicted human location is the index with the largest amplitude.
- Among all 64 sets of tests, 58 recovered signals indicate the correct locations.
- 90.6% zone-level positioning accuracy.



Discussion

- The error happens when two zones are neighbored.
- When testing, due to the posture or miss alignment of the standing point, the radiation from human may affect the neighboring zone.
- Also, the thickness of the 3D printed mask may block partial received energy, especially for the zones at the outer circle.

Summary

- We propose a low-cost, compressive-sensing based method for indoor human positioning using a single thermopile pixel sensor.
- Using a random coded binary mask to compressively sample the IR radiation of the test scene.
- Utilizing the reconstruction algorithm, the locations of the human target are assigned to the index of the largest amplitude.
- Proposed system can reach 90.6% zone-level positioning accuracy.

Future work

- Increase the detection area.
- Study the case when multiple persons are present.
- Optimize the physical design of the sensor
- Study reconstruct algorithms that do not need prior knowledge of sparsity and reduce the computation complexity.
- Optimize the mask design.

Thank you!

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