GroupCoach: Compressed Sensing Based Group Activity Monitoring and Correction

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上海交通大學
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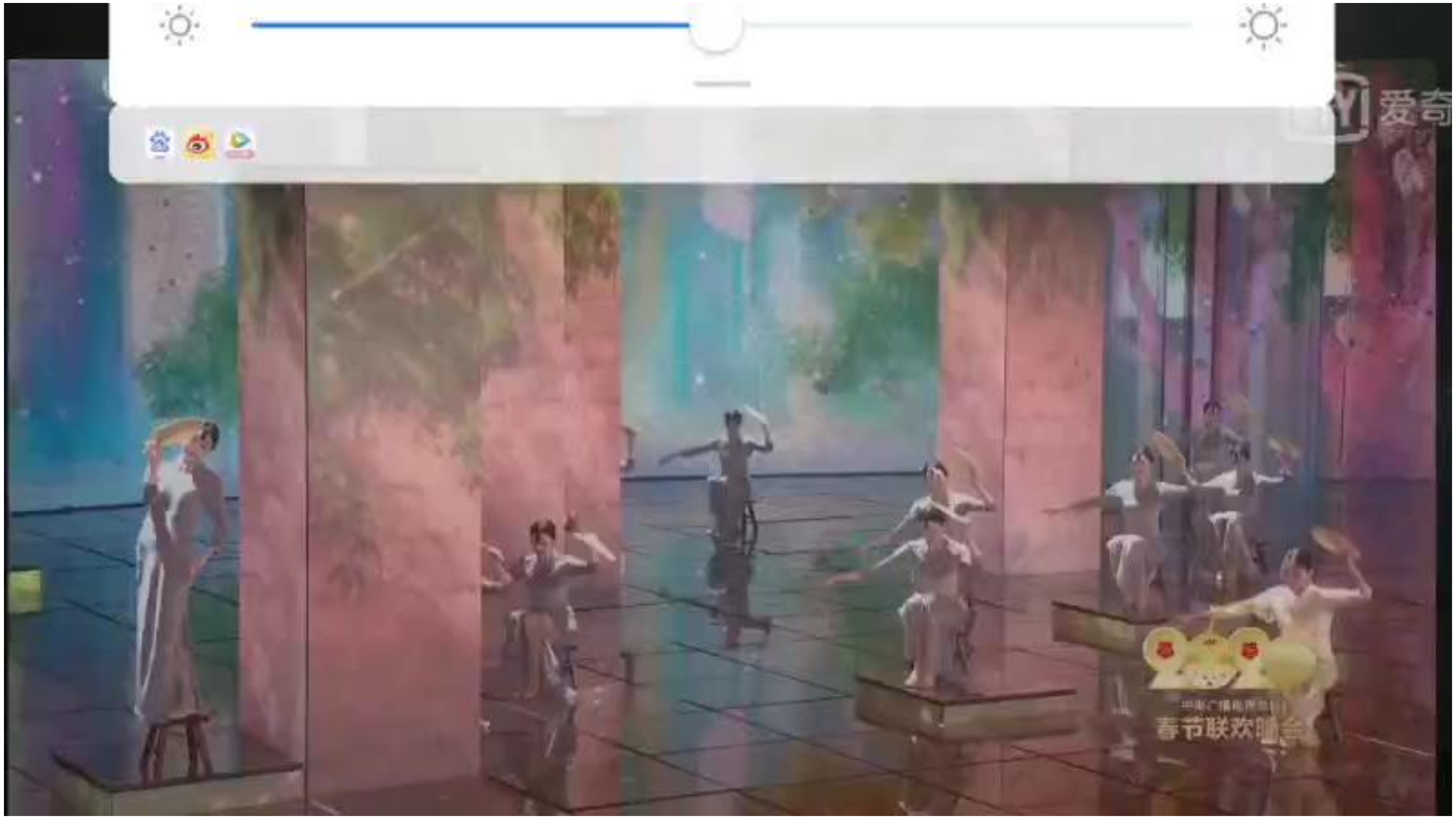
Background: Group Activity



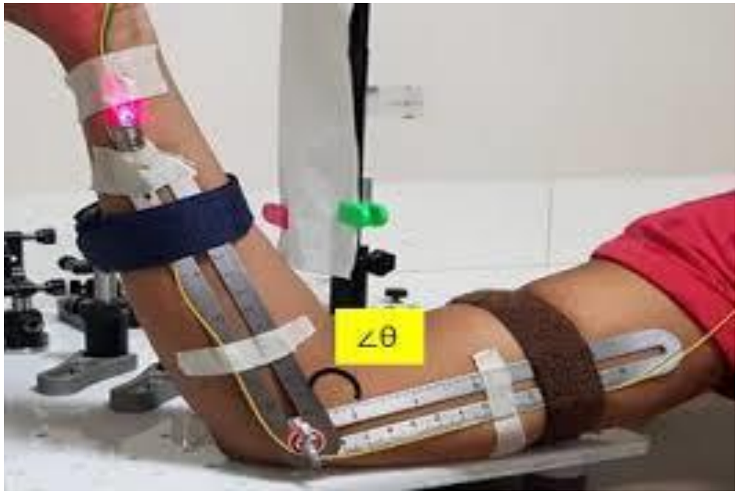
Background: Group Activity

18 dancers with 3 coaches and 2 directors

Their grand scale presents beauty, but with the hardness of rehearsal.

Background: Multi-people Motion Tracking

- **Vision-based motion tracking**
  - Tools: cameras, depth sensors, infrared projectors.
  - Example: Microsoft Kinect
  - Limitations: Pre-trained model required, computationally expensive for multiple targets.



- **Sensor-based motion tracking**
  - Fibre-optic, joint bend body sensors (wired): accurate transmission with limited motion range and speed
  - Wireless body area network (WBAN): flexible transmission with light-weight deployment

Background: Multi-people Motion Tracking

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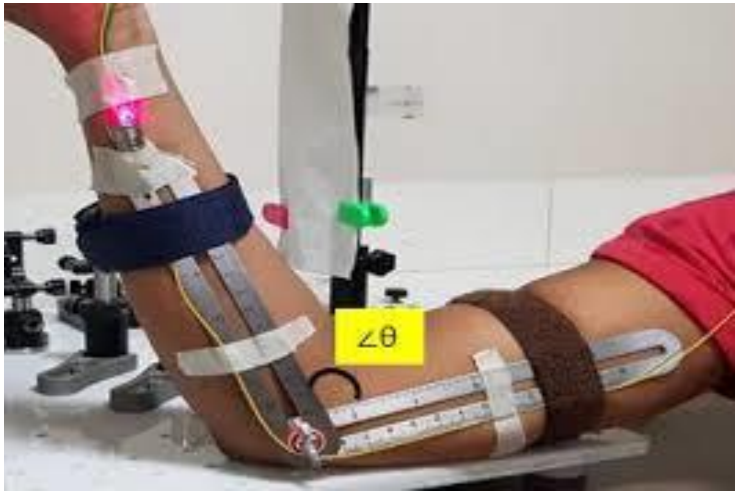

- **Sensor-based motion tracking**
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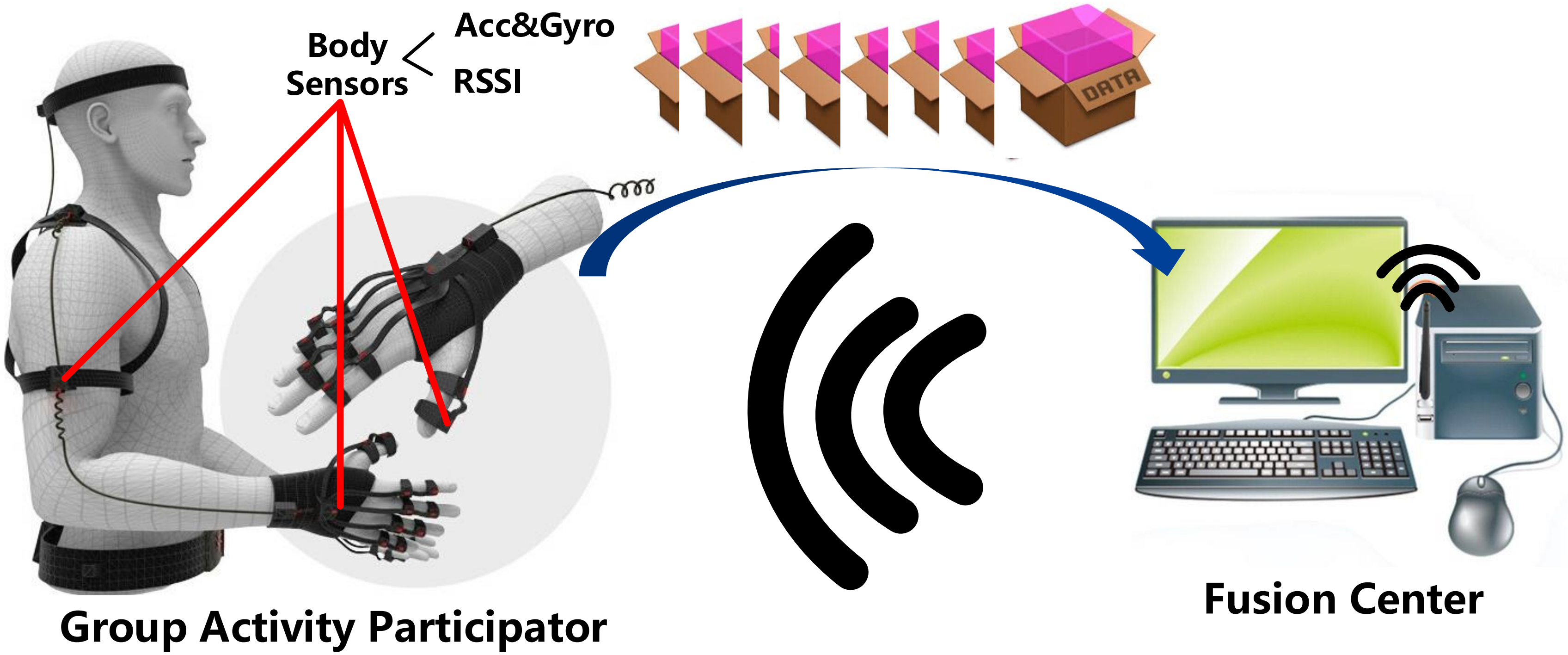
Background: WBAN Scheme



Acc & Gyro: Motion accelerations and directions

RSSI: Location estimation

Background: QoS Challenges

- Less consumption
  - Reason: Limited sensor power supply
  - Strategy: Energy-efficient sensing strategy
- Higher accuracy
  - Reason: Transmission interferences
  - Strategy: Optimized data reconstruction
- Lower latency
  - Reason: Dynamic activity monitoring environment
  - Strategy: Lower computational complexity and lower transmission amount

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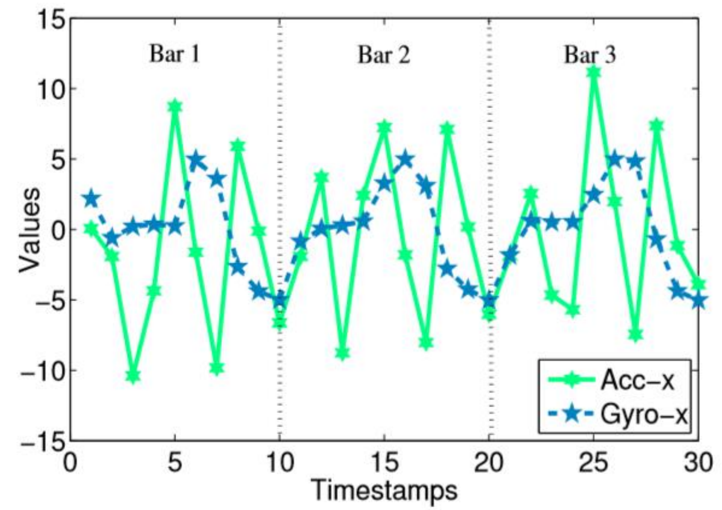
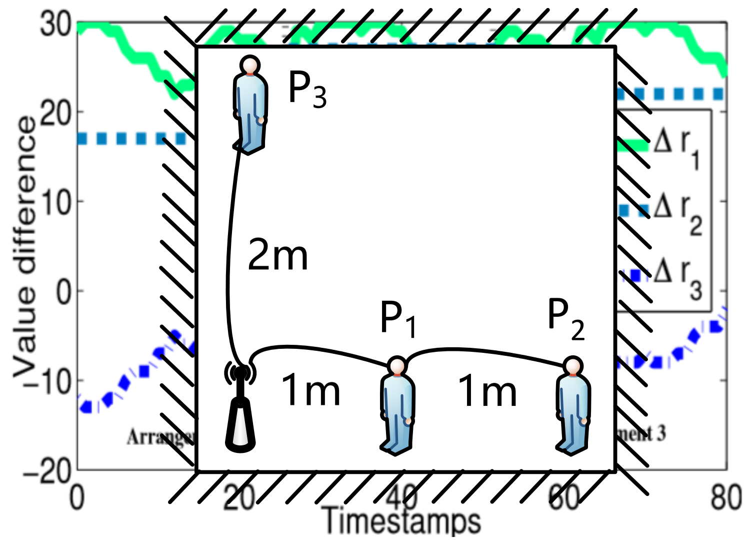
Motivation: Spatial & Temporal Stabilities

- **Inertial sensory data (Temporal)**
  - Values are replicated among bars of background music.

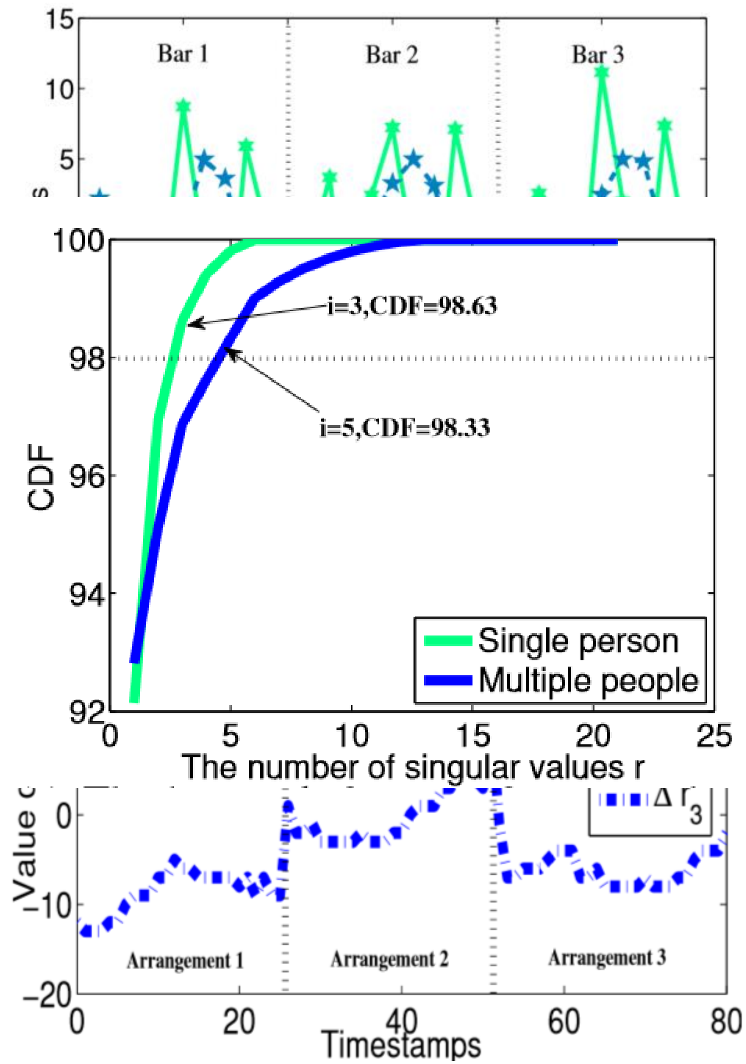


- **Channel sensory data (Spatial)**
  - Value differences between adjacent participants are fixed w.r.t. time, but related to their relative locations.



Motivation: Low Rankness

- **Inertial sensory data (Temporal)**
  - Values are replicated among bars of background music.
  - The rank of the whole song equals to the rank of one bar.
- **Channel sensory data (Spatial)**
  - Value differences between adjacent participants are fixed w.r.t. time, but related to their relative locations.
  - The rank of the whole team can be transformed to the rank of their relative locations.



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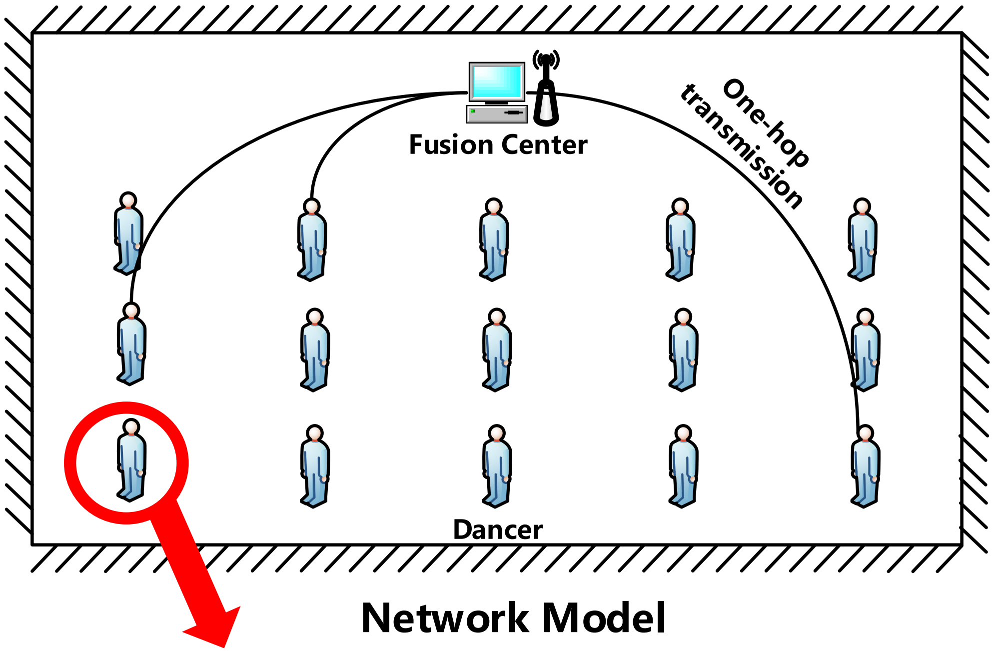
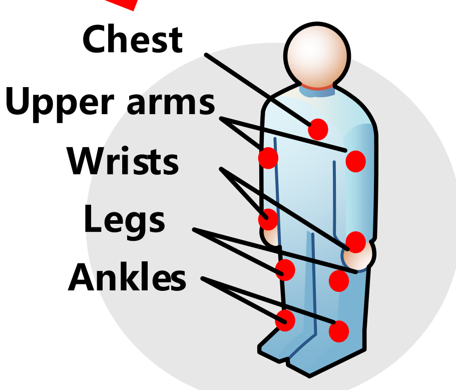
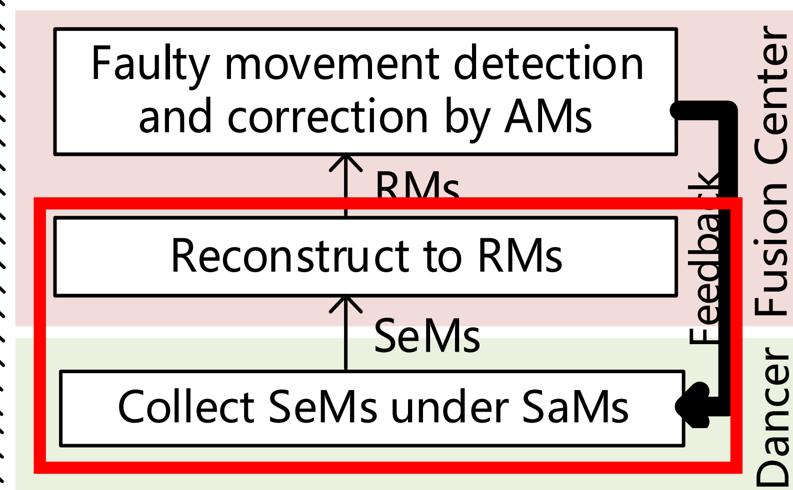
Design Overview



Network Model





System Overview

SeM: Sensory Matrix
SaM: Sampling Matrix
RM: Reconstructed Matrix
AM: Anchor Matrix

Design: CS-based Data Reconstruction

- Under SaMs, the sensors transmit SeMs to the fusion center:

$$A \circ M_A = S_A$$

- The problem of data reconstruction is:

Given SeMs and SaMs, the optimal RMs are considered to have the minimum difference with OMs, formulated as:

$$\begin{array}{ll} \text{Objective:} & \min \left\| A - \hat{A} \right\|_F \\ \text{Subject to:} & S_A, M_A, \end{array}$$

- Due to the sparsity of sensory data, the RMs can be diagonally transformed as:

$$\hat{A} = \hat{U}\hat{H}\hat{V} = \hat{U}\hat{H}^{\frac{1}{2}} \cdot \hat{H}^{\frac{1}{2}}\hat{V} = LR^T$$

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- Using the relaxation of Lagrange multiplier and the tuning parameter λ_1, the optimization target becomes:

$$\min(\left\|(LR^T) \circ M_A - S_A\right\|_F^2 + \lambda_1(\|L\|_F^2 + \|R\|_F^2)).$$

Recall: Spatial & Temporal Stabilities

- **Inertial sensory data (Temporal)**
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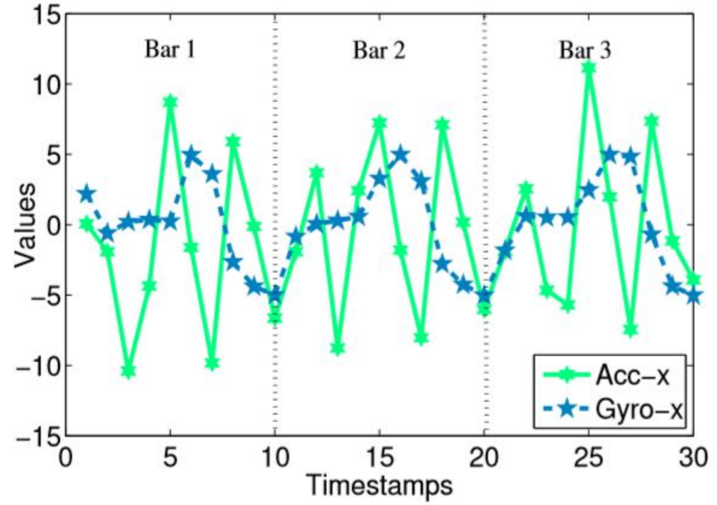

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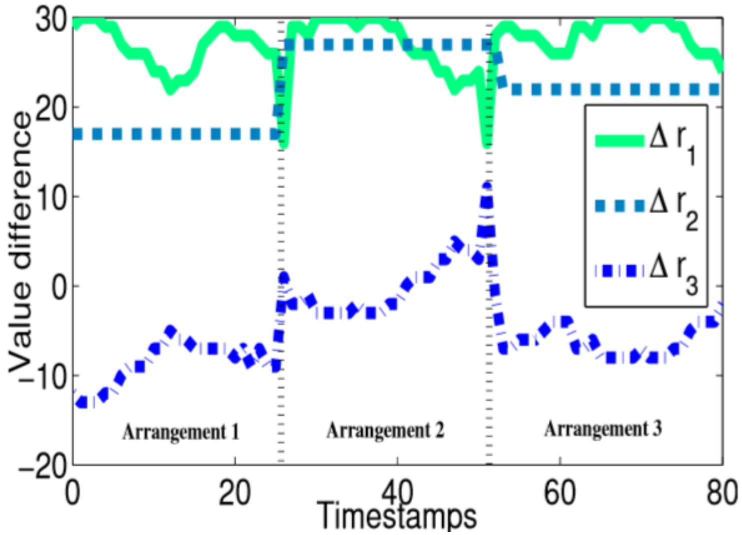


Design: Stabilities-Driven Data Reconstruction

- When we measure the temporal stability by matrix Θ :

$$\begin{bmatrix} \overbrace{\begin{matrix} 1 & 0 & \cdots & -1 \end{matrix}}^{\frac{T}{B}} & \begin{matrix} 0 & \cdots & 0 \end{matrix} \\ \begin{matrix} 0 & 1 & 0 & \cdots \end{matrix} & \begin{matrix} -1 & 0 & \cdots \end{matrix} \\ \begin{matrix} \vdots & \vdots & \vdots & \ddots \end{matrix} & \begin{matrix} \vdots & \vdots & \vdots \end{matrix} \\ \begin{matrix} 0 & 0 & \cdots & 1 \end{matrix} & \begin{matrix} 0 & \cdots & -1 \end{matrix} \end{bmatrix}_{3PN \times 3PN} ;$$

The optimization target for inertial sensory data becomes:

$$\min(\left\|(LR^T) \circ M_A - S_A\right\|_F^2 + \lambda_1(\|L\|_F^2 + \|R\|_F^2)) \\ +\lambda_2(\left\|LR^T\Theta\right\|_F^2),$$

Design: Stabilities-Driven Data Reconstruction

- When we measure the spatial stability by matrix T and ΔR :

$$\boxed{\Delta r(i,t) = 10\eta \lg \frac{d_{(i,t)}}{d_{(1,t)}} + (i-1)X_B}$$

$$T = \begin{bmatrix} 1 & -1 & 0 & \cdots & 0 \\ 0 & 1 & -1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 1 & -1 \end{bmatrix}_{N\times\beta T} \qquad \Delta R = \begin{bmatrix} \Delta r(1,1) & \Delta r(1,2) & \cdots & \Delta r(1,\beta T) \\ \Delta r(2,1) & \Delta r(2,2) & \cdots & \Delta r(2,\beta T) \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 \end{bmatrix}_{N\times\beta T}$$

The optimization target for channel sensory data becomes:

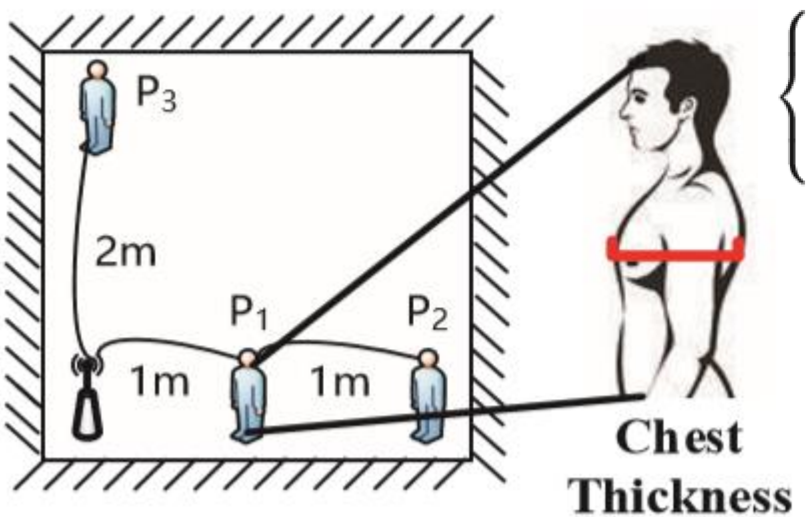
$$\begin{aligned} \min(\left\|(LR^T)\circ M_A - S_A\right\|_F^2 + \lambda_1(\|L\|_F^2 + \|R\|_F^2)) \\ +\lambda_2(\left\|TLR^T - \Delta R\right\|_F^2), \end{aligned}$$

Design: Body Impact Factor

- The mapping between RSSI value and the distance d

[log-normal shadow model]:

$$PL(d)(dB) = \overline{PL}(d_0) + 10\eta \lg(\frac{d}{d_0}) + X_E + mX_B$$
$$= E + 10\eta \lg(\frac{d}{d_0}) + mX_B.$$



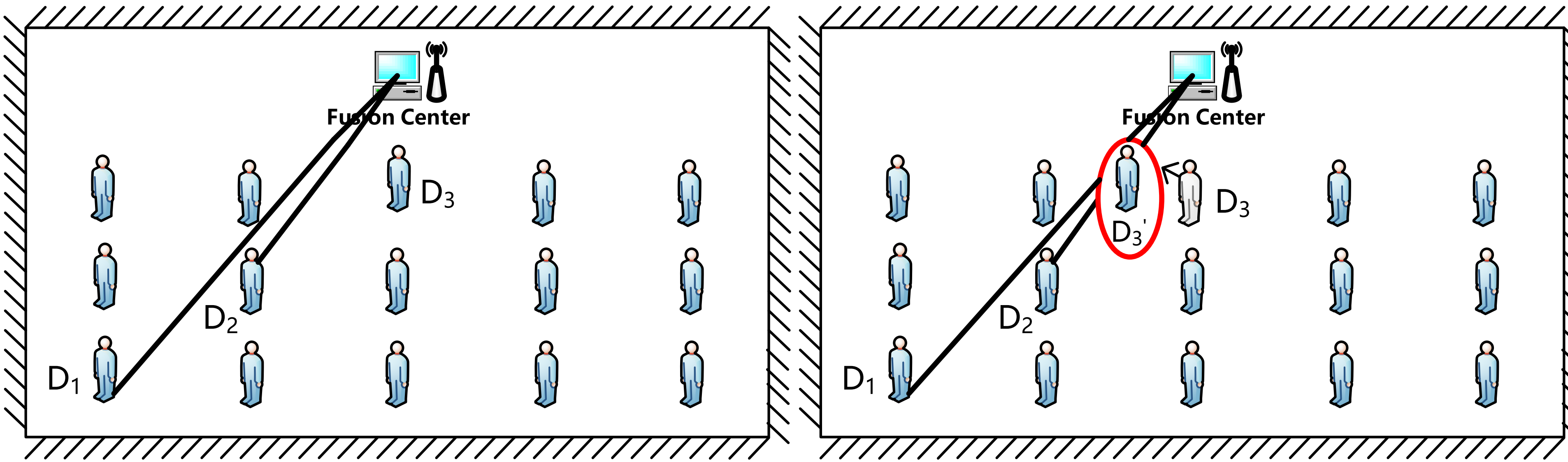
$$\begin{cases} \overline{R_{P_1}} = E \\ \overline{R_{P_2}} = E + 10\eta \lg 2 + X_B \\ \overline{R_{P_3}} = E + 10\eta \lg 2 \end{cases} \Rightarrow \begin{cases} E = \overline{R_{P_1}} \\ X_B = \overline{R_{P_2}} - \overline{R_{P_3}} \\ \eta = \frac{\overline{R_{P_3}} - \overline{R_{P_1}}}{10 \lg 2} \end{cases}$$

Thickness	10cm[1]	20cm	30cm	40cm
X_B	-5	-6	-17	-20

[1] For system extension, we also measure the thickness except chest, such as arm or leg.

Design: Body Impacted Near-to-Far (BINF) Diffusion Model

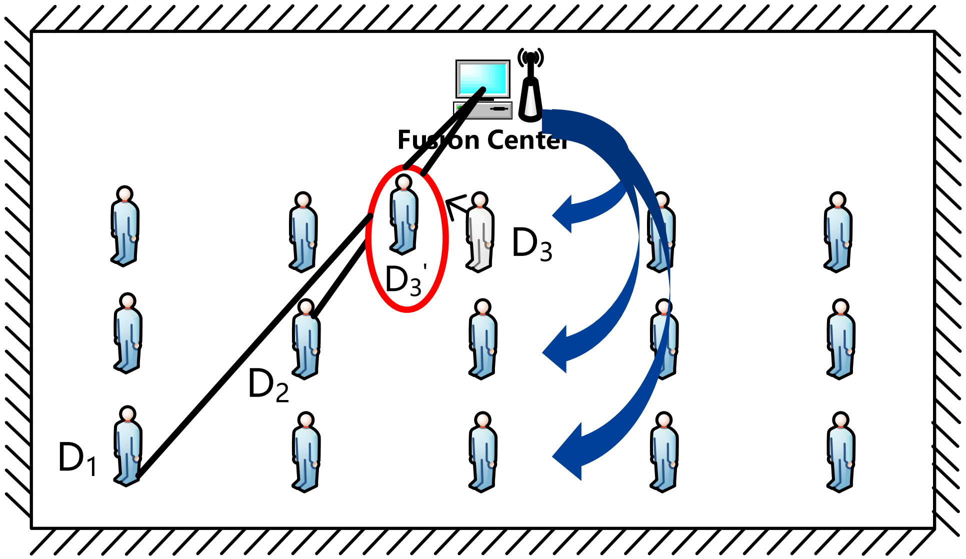
- Challenge:



New shielding situation leads to inaccurate faulty detection.

Design: Body Impacted Near-to-Far (BINF) Diffusion Model

- Solution:



Near to far calculation, and update AMs step-by-step.

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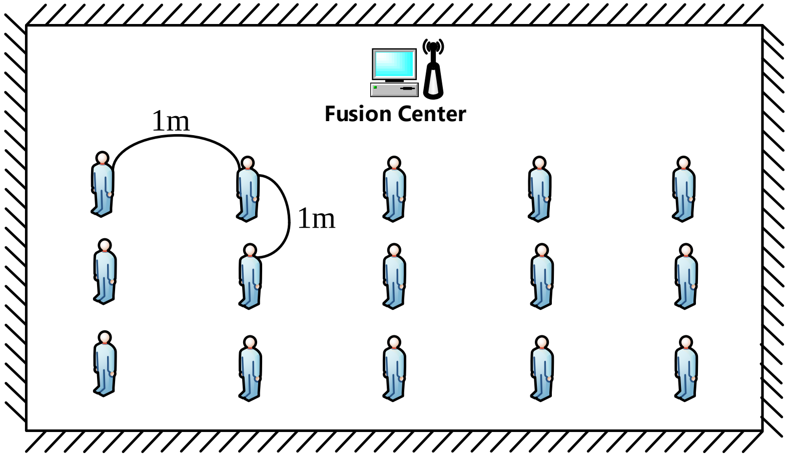
Evaluation settings

- Emulation data collection:
  - 3 volunteers with required motions

  [1 totally right, 1 motion wrong, 1 both motion and location wrong]
  - Emulated to 9 people with arranged locations and right motions



- 9 off-the-shelf smartwatches on each body with Android data collection program
- Matlab code for data reconstruction on Thinkpad Carbon X1 laptop
  - http://www.cs.sjtu.edu.cn/~linghe.kong/GroupCoach.rar

Recall: QoS Challenges

- Less consumption
  - Reason: Limited sensor power supply
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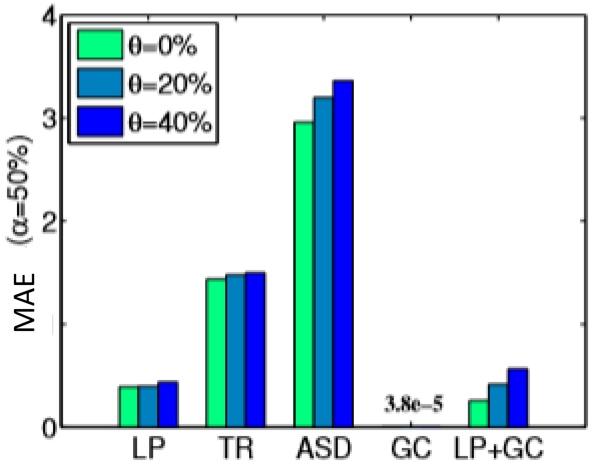
Evaluation results: Accuracy for reconstruction

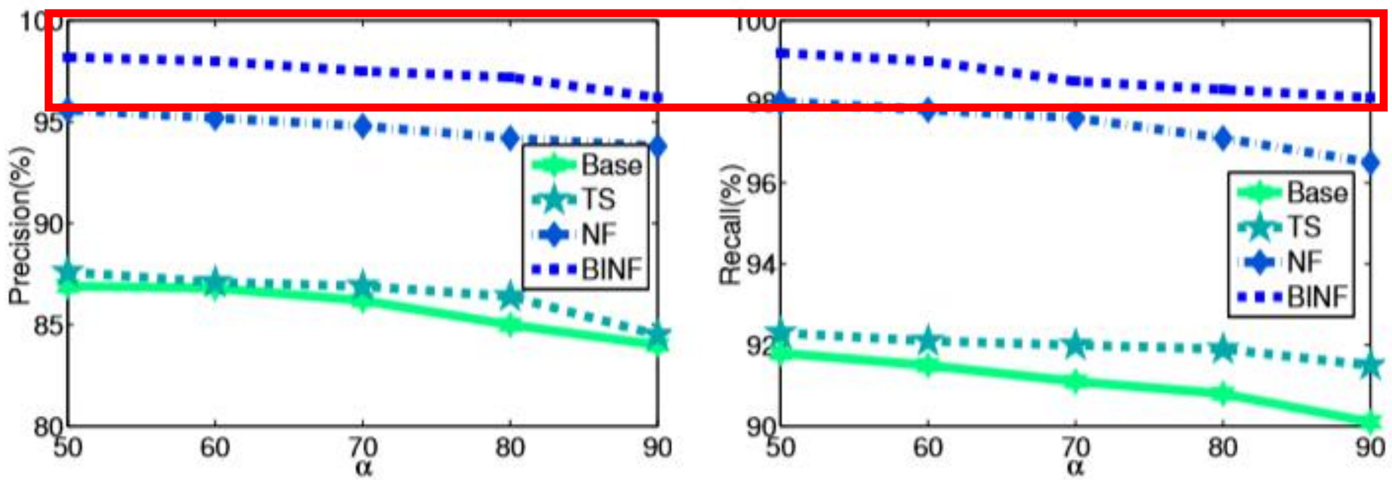
$\alpha(\%)$	50	60	70	80	90
LP	0.3918	0.4852	0.7036	1.1169	1.6022
TR	1.4414	1.4821	1.5100	1.6521	1.7001
ASD	2.9565	3.1260	3.3715	3.6242	4.1115
GroupCoach	$3.83e^{-5}$	$4.4e^{-5}$	$5.49e^{-5}$	**0.0210**	**0.0031**

The **Mean Absolute Error (MAE)** for linear interpolation (LP), tensor based reconstruction (TR), ASD without stability consideration (ASD), and reconstruction in GroupCoach, with different compression ratio α.



The accuracy comparison with different missing ratio θ.

Evaluation results: Accuracy for detection & Latency



(a) Precision (b) Recall

The **Precision & Recall** for Baseline (Base), Time Sequence (TS), NF, and BINF in GroupCoach, with different compression ratio α.

Reconstruction		Detection & Correction	
LP	$1.16e^{-4}$	Base	0.17
TR	3.2	TS	2.06
ASD	0.1943	NF	0.95
GC	**0.866**	**BINF**	**0.97**

Contents

Conclusion & Future Work

- **Conclusion**
  - The exploration of the **spatial and temporal stabilities** in group activities, **low-rankness** of sensory data, making **the appliance of CS** into group activities possible.
  - A new **BINF diffusion model** to solve channel attenuation problem caused by body shielding.
  - A **comprehensive** CS-based group activity monitoring and correction system.
- **Future Work**
  - **Outdoor extension with changed environment factor**
  - **Detection scale extension with multi-hop transmission**

Thanks for listening！

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