GroupCoach: Compressed Sensing Based Group Activity Monitoring and Correction

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2 Motivation
3 Design
4 Evaluation
5 Conclusion & Future Work
Background: Group Activity
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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

- **Vision-based 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

Group Activity Participator

Fusion Center
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.
Design Overview

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:

\[
\text{Objective: } \min \| A - \hat{A} \|_F \\
\text{Subject to: } S_A, M_A,
\]

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

\[
\hat{A} = \hat{U} \hat{H} \hat{V} = \hat{U} \hat{H}^{\frac{1}{2}} \cdot \hat{H}^{\frac{1}{2}} \hat{V} = LR^T
\]
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 minimum difference with OMs, formulated as:

  \[
  \begin{align*}
  \text{Objective: } & \quad \min \| A - \hat{A} \|_F \\
  \text{Subject to: } & \quad S_A, M_A, \\
  \text{Objective: } & \quad \min (\| L \|_F^2 + \| R \|_F^2) \\
  \text{Subject to: } & \quad (LR^T) \circ M_A = S_A.
  \end{align*}
  \]

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

  \[ \hat{A} = \hat{U} \hat{H} \hat{V} = \hat{U} \hat{H}^{\frac{1}{2}} \cdot \hat{H}^{\frac{1}{2}} \hat{V} = LR^T \]
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 minimum difference with OMs, formulated as:

- Using the relaxation of Lagrange multiplier and the tuning parameter \( \lambda_1 \), the optimization target becomes:

\[
\min \left( \| (LR^T) \circ M_A - S_A \|_F^2 + \lambda_1 (\| L \|_F^2 + \| R \|_F^2) \right).
\]
Recall: 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.
Design: Stabilities-Driven Data Reconstruction

- When we measure the temporal stability by matrix $\Theta$:

$$
\begin{bmatrix}
1 & 0 & \cdots & -1 & 0 & \cdots & 0 \\
0 & 1 & 0 & \cdots & -1 & 0 & \cdots \\
\vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots \\
0 & 0 & \cdots & 1 & 0 & \cdots & -1
\end{bmatrix}_{3PN \times 3PN}
$$

The optimization target for inertial sensory data becomes:

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

- When we measure the spatial stability by matrix $T$ and $\Delta R$:

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

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

The optimization target for channel sensory data becomes:

$$ \min \left( \left\| (LR^T) \circ M_A - S_A \right\|_F^2 + \lambda_1 \left( \left\| L \right\|_F^2 + \left\| R \right\|_F^2 \right) \right) + \lambda_2 \left( \left\| TLR^T - \Delta R \right\|_F^2 \right), \quad \lambda_1, \lambda_2 > 0 $$
Design: Body Impact Factor

- The mapping between RSSI value and the distance $d$ [log-normal shadow model]:

$$PL(d)(dB) = PL(d_0) + 10\eta \log\left(\frac{d}{d_0}\right) + X_E + mX_B$$

$$= E + 10\eta \log\left(\frac{d}{d_0}\right) + mX_B.$$ 

\[
\begin{align*}
\frac{R_{P_1}}{R_{P_2}} &= E + 10\eta \log 2 + X_B \\
\frac{R_{P_2}}{R_{P_3}} &= E + 10\eta \log 2
\end{align*}
\]

\[
\Rightarrow \begin{align*}
E &= \frac{R_{P_1}}{R_{P_2}} \\
X_B &= \frac{R_{P_2}}{R_{P_3}} - \frac{R_{P_1}}{R_{P_3}} \\
\eta &= \frac{R_{P_3} - R_{P_1}}{10 \log 2}
\end{align*}
\]

<table>
<thead>
<tr>
<th>Thickness</th>
<th>10cm$^1$</th>
<th>20cm</th>
<th>30cm</th>
<th>40cm</th>
</tr>
</thead>
<tbody>
<tr>
<td>$X_B$</td>
<td>-5</td>
<td>-6</td>
<td>-17</td>
<td>-20</td>
</tr>
</tbody>
</table>

$^1$ 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.
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
  ▪ 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
Evaluation results: Accuracy for reconstruction

<table>
<thead>
<tr>
<th>α(%)</th>
<th>50</th>
<th>60</th>
<th>70</th>
<th>80</th>
<th>90</th>
</tr>
</thead>
<tbody>
<tr>
<td>LP</td>
<td>0.3918</td>
<td>0.4852</td>
<td>0.7036</td>
<td>1.1169</td>
<td>1.6022</td>
</tr>
<tr>
<td>TR</td>
<td>1.4414</td>
<td>1.4821</td>
<td>1.5100</td>
<td>1.6521</td>
<td>1.7001</td>
</tr>
<tr>
<td>ASD</td>
<td>2.9565</td>
<td>3.1260</td>
<td>3.3715</td>
<td>3.6242</td>
<td>4.1115</td>
</tr>
<tr>
<td>GroupCoach</td>
<td>3.83e-5</td>
<td>4.4e-5</td>
<td>5.49e-5</td>
<td><strong>0.0210</strong></td>
<td><strong>0.0031</strong></td>
</tr>
</tbody>
</table>

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

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

<table>
<thead>
<tr>
<th>Reconstruction</th>
<th>Detection &amp; Correction</th>
</tr>
</thead>
<tbody>
<tr>
<td>LP</td>
<td>$1.16e^{-4}$</td>
</tr>
<tr>
<td>TR</td>
<td>3.2</td>
</tr>
<tr>
<td>ASD</td>
<td>0.1943</td>
</tr>
<tr>
<td>GC</td>
<td>0.866</td>
</tr>
<tr>
<td>Base</td>
<td>0.17</td>
</tr>
<tr>
<td>TS</td>
<td>2.06</td>
</tr>
<tr>
<td>NF</td>
<td>0.95</td>
</tr>
<tr>
<td>BINF</td>
<td>0.97</td>
</tr>
</tbody>
</table>
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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