Deploying Distributed Real-time Healthcare Applications on Wireless Body Sensor Networks

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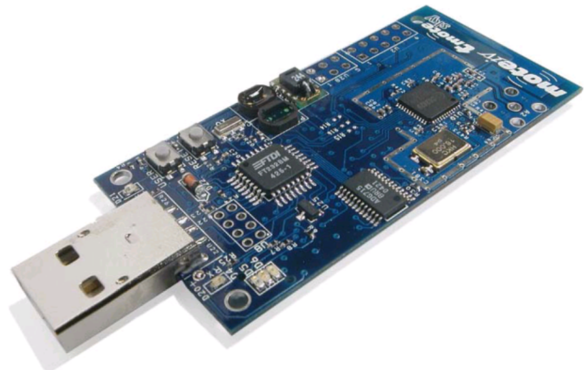
Team for Research in Ubiquitous Secure Technology

Body Sensor Networks

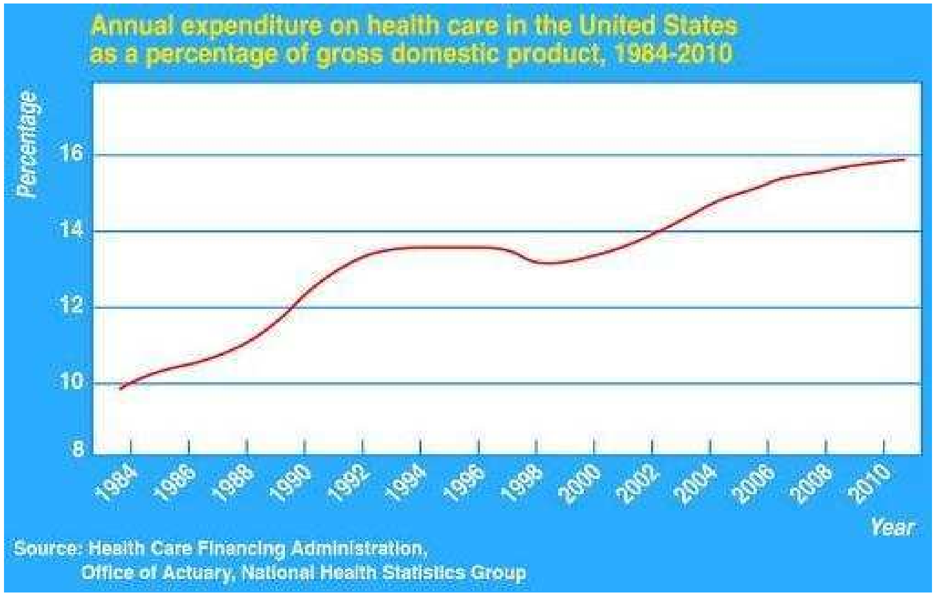
- Potential to **revolutionize healthcare**
  - Reduce cost
  - Reduce physical barriers
  - Improve quality of care



- Enabling
  - Prevention
  - Detailed monitoring
  - Continuous, real-time reporting

Motivation

- Health care expenditures rising
  - 15.9% of the US GDP ($2.6 trillion) by 2010
  - Cost of health care is a national concern



System Requirements

TRUST
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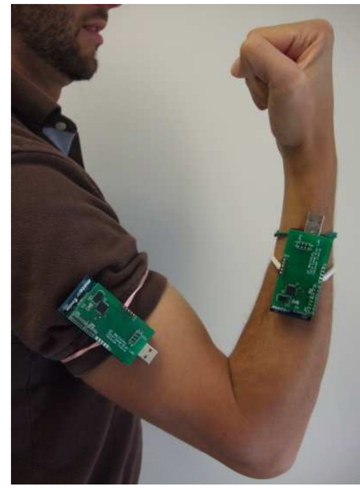
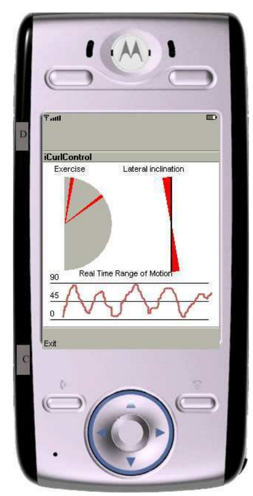
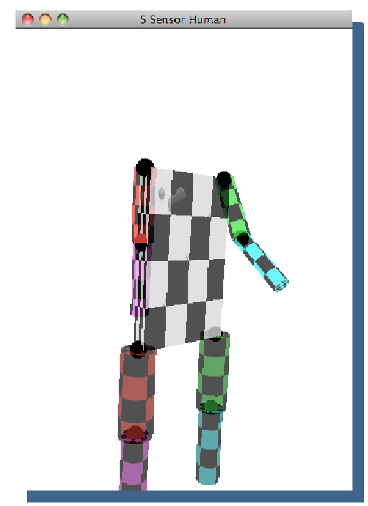
- Deployable
  - Home
  - Hospital
- Reliable and Accurate
  - Research
  - Clinical
- Private
  - Legal Restrictions
  - Social Concerns







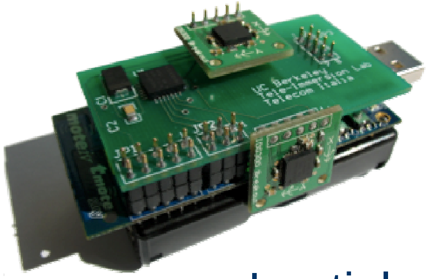
Applications

- **Assisted Living**
  - Fall Detection and Prevention
  - Parkinson’s Disease
- **Motion Analysis**
  - Gait Analysis
  - Balance
  - Muscular Dystrophy
- **Remote Patient Monitoring**
  - Rehabilitation
  - Physical Therapy
  - In-Hospital Surgery Recovery
  - Metabolism

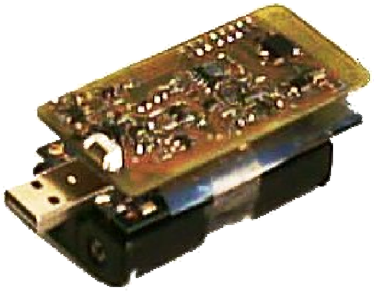
Hardware

- Java-compatible base station

- 802.15.4 device running TinyOS



Inertial Sensor

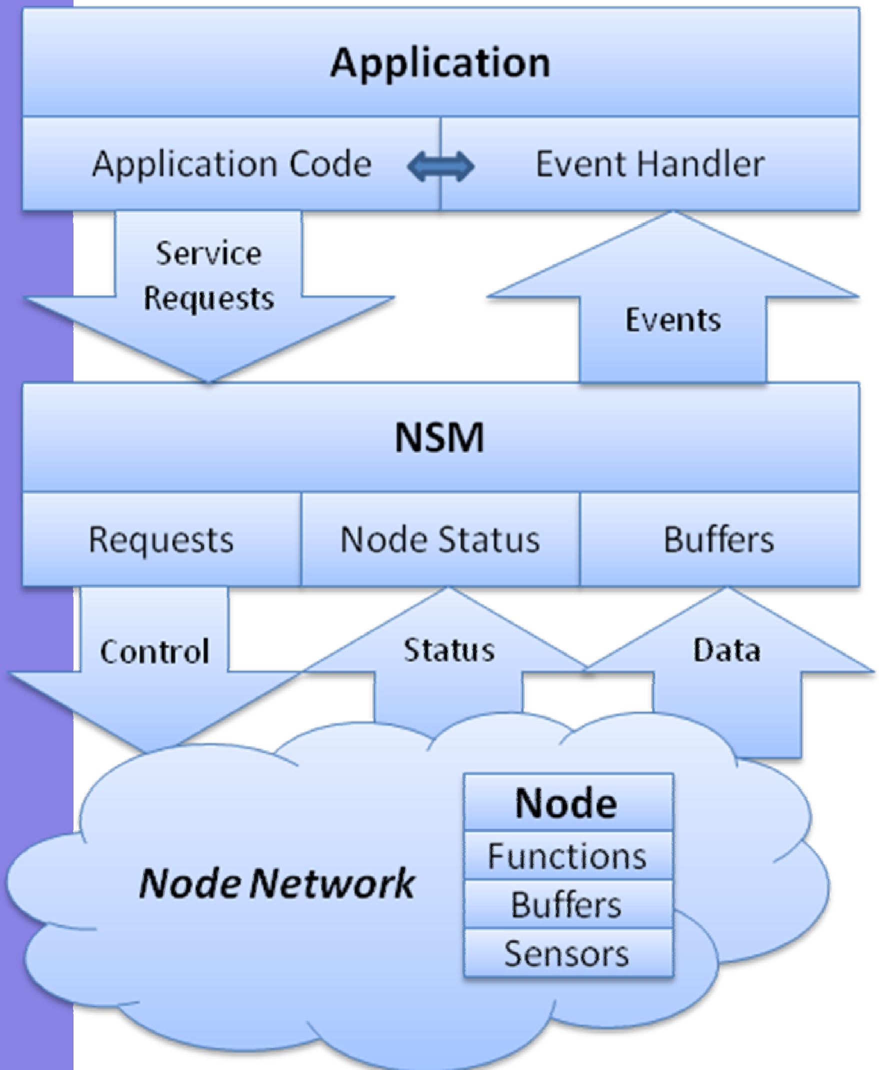


Bio-sensor

Software

- Application development framework
- Abstraction for developers
  - Focus on signal processing
  - Hardware independent
  - Modular and extensible
- Developed as open-source
  - http://spine.tilab.com

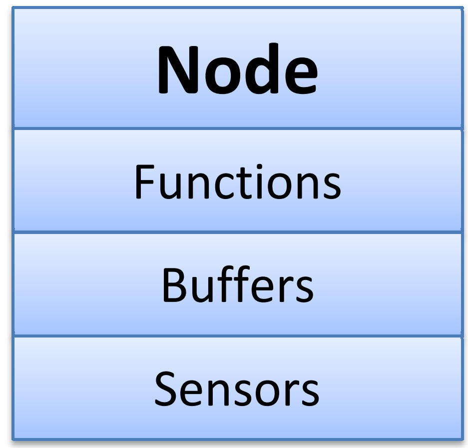
Software



- The **application** makes **service requests**
- The **NSM (Network Service Manager)** coordinates the nodes and responds via **events**
- The **nodes** perform local sensing and processing

Software

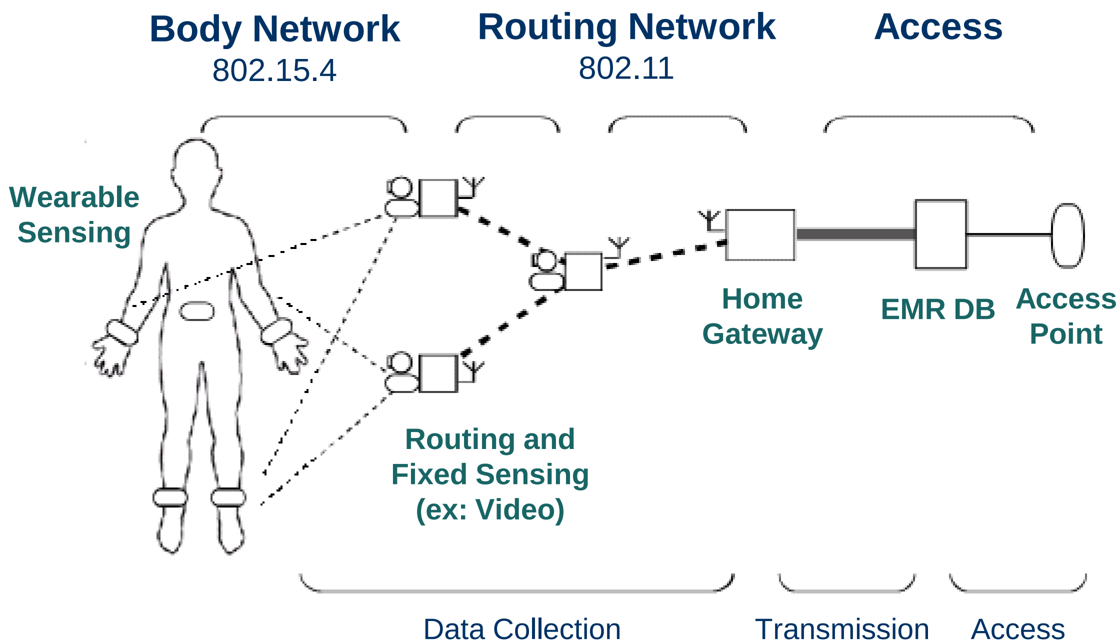
- Requests allow developer to specify:
  - Sensors to query
  - Sampling rate
  - Latency constraints
  - Local processing



- Local Functions:
  - Processing algorithms
  - Local data storage
  - Logic to control communication

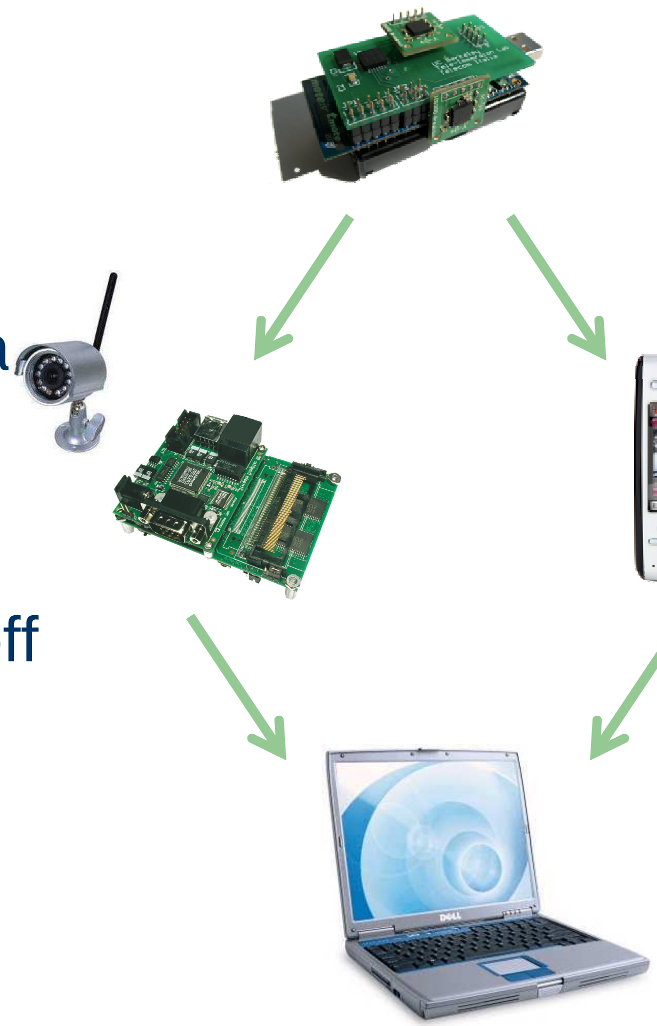
Deployment

- CareNet
  - On-body nodes
  - 802.11 Wi-Fi network



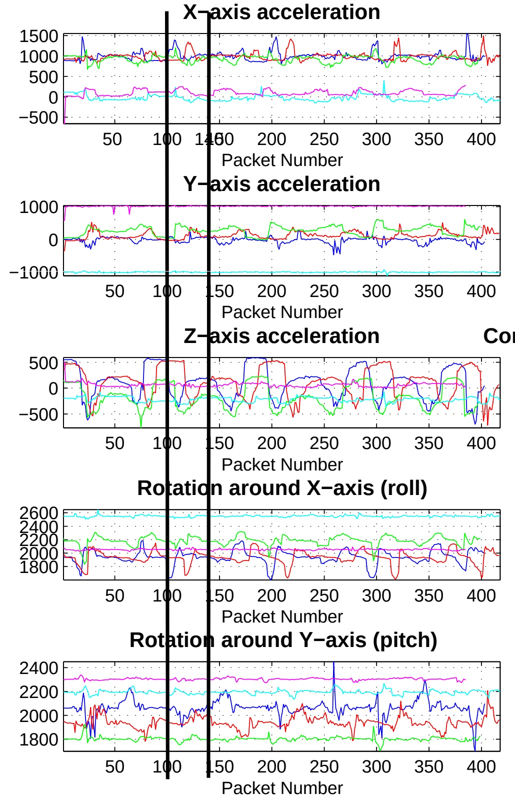
Deployment

- Advantages
  - Fast deployment
  - Easily extensible
  - Standard 802.11 interfa
- Architecture provides
  - Automatic node hand-off
  - Packet routing
  - Built-in security



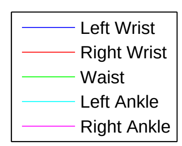
Deployment

- Proof-of-Concept at Vanderbilt Homecare



Corresponding Image when Receiving No.100 Movement Packet

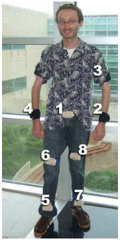
Corresponding Image when Receiving No.140 Movement Packet

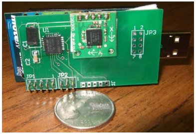


Problem Formulation: Distributed Action Recognition

Architecture

- Eight sensors on human body.
- Locations are given and fixed.
- Each sensor carries triaxial accelerometer and biaxial gyroscope.
- Sampling frequency: 20Hz.





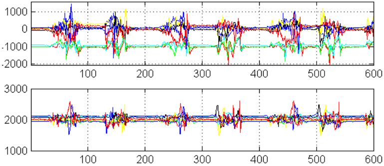


Figure: Readings from 8 x-axis accelerometers and x-axis gyroscopes for a *stand-kneel-stand* sequence.

Challenges

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4. **Identity independence**:

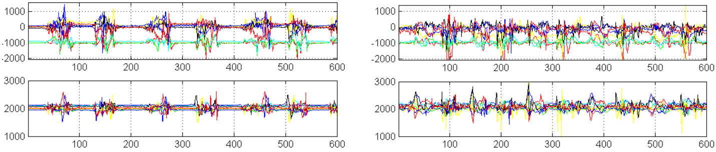

Figure: Same actions performed by two subjects.

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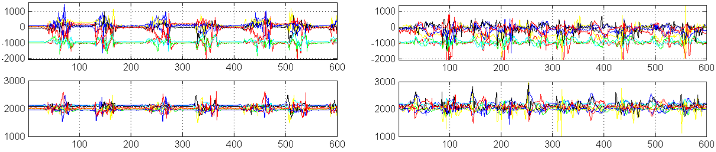

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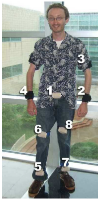
Proposed solutions:

1. 10-D LDA feature space suffices to express 12 action classes on individual motes.
2. Individual sensor obtains limited classification ability.
   To save power, sensors become active only when certain events are locally detected.
3. Global classifier adapts to change of active sensors in network.

Experiment Results

Precision vs Recall:

Sensors	2	7	2,7	1,2,7	1- 3, 7,8	1- 8
Prec [%]	89.8	94.6	94.4	92.8	94.6	98.8
Rec [%]	65	61.5	82.5	80.6	89.5	94.2



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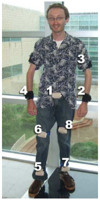
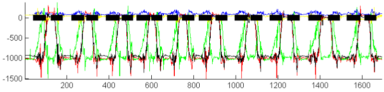
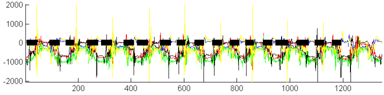


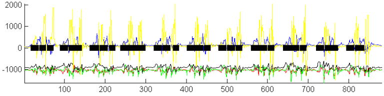
Segmentation results using all 8 sensors:



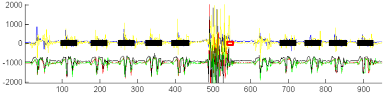
(a) Stand-Sit-Stand



(b) Sit-Lie-Sit



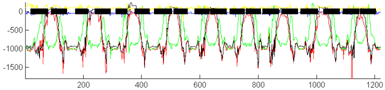
(c) Rotate-Left



(d) Go-Downstairs

Mixture Subspace Model for Distributed Action Recognition

1. **Training samples**: manually segment and normalize to duration h.



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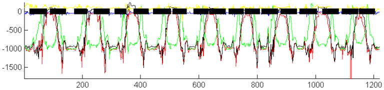

2. On each sensor node i, **stack training actions** into vector form

$$\mathbf{v}_i = [x(1), \cdots, x(h), y(1), \cdots, y(h), z(1), \cdots, z(h), \theta(1), \cdots, \theta(h), \rho(1), \cdots, \rho(h)]^T \in \mathbb{R}^{5h}$$

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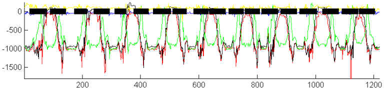

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3. **Full body motion**

$$\text{Training sample: } \mathbf{v} = \begin{pmatrix} \mathbf{v}_1 \\ \vdots \\ \mathbf{v}_8 \end{pmatrix} \quad \text{Test sample: } \mathbf{y} = \begin{pmatrix} \mathbf{y}_1 \\ \vdots \\ \mathbf{y}_8 \end{pmatrix} \in \mathbb{R}^{8 \cdot 5h}$$

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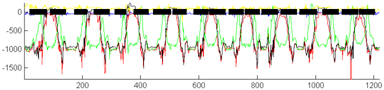

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4. **Action subspace**: If $\mathbf{y}$ is from Class i,

$$\mathbf{y} = \begin{pmatrix} \mathbf{y}_1 \\ \vdots \\ \mathbf{y}_8 \end{pmatrix} = \alpha_{i,1} \begin{pmatrix} \mathbf{v}_1 \\ \vdots \\ \mathbf{v}_8 \end{pmatrix}_1 + \cdots + \alpha_{i,n_i} \begin{pmatrix} \mathbf{v}_1 \\ \vdots \\ \mathbf{v}_8 \end{pmatrix}_{n_i} = A_i \alpha_i.$$

Sparse Representation

1. Nevertheless, label($\mathbf{y}$) $= i$ is the **unknown** membership function to solve:

$$\text{Sparse Representation:} \quad \mathbf{y} = \begin{bmatrix} A_1 & A_2 & \cdots & A_K \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_K \end{bmatrix} = A\mathbf{x} \in \mathbb{R}^{8 \cdot 5h}.$$

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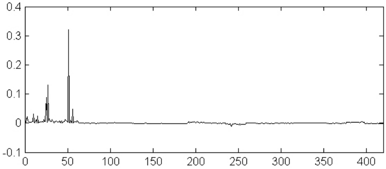

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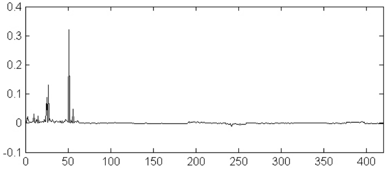

Sparse representation encodes membership.

3. **Two problems**:
   - Directly solving the linear system is intractable.
   - Seeking the sparsest solution.

Dimensionality Reduction

1. Construct **Fisher/LDA** features $R_i \in \mathbb{R}^{10\times 5h}$ on each node:

$$\tilde{\mathbf{y}}_i = R_i\mathbf{y}_i = R_iA_i\mathbf{x} = \tilde{A}_i\mathbf{x} \in \mathbb{R}^{10}$$

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2. Globally

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3. During the transformation, the data matrix A and $\mathbf{x}$ remain *unchanged*.

Seeking Sparsest Solution: ℓ^1-Minimization

1. Ideal solution: ℓ^0-minimization

$$(P_0) \quad \mathbf{x}^* = \arg\min_{\mathbf{x}} \|\mathbf{x}\|_0 \text{ s.t. } \tilde{\mathbf{y}} = \tilde{A}\mathbf{x}.$$

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However, such solution is generally *NP-hard*.

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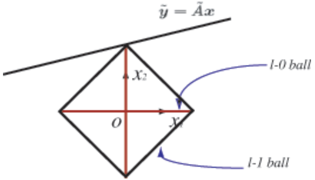
3. ℓ^1-Ball

- ℓ^1-Minimization is convex.
- Solution equal to ℓ^0-minimization.



A Distributed Recognition Framework

1. **Distributed Sparse Representation**

$$\begin{pmatrix} \mathbf{y}_1 \\ \vdots \\ \mathbf{y}_8 \end{pmatrix} = \left(\begin{pmatrix} \mathbf{v}_1 \\ \vdots \\ \mathbf{v}_8 \end{pmatrix}_1, \cdots, \begin{pmatrix} \mathbf{v}_1 \\ \vdots \\ \mathbf{v}_8 \end{pmatrix}_n \right) \mathbf{x} \Leftrightarrow \begin{cases} \mathbf{y}_1 = (\mathbf{v}_{1,1}, \cdots, \mathbf{v}_{1,n})\mathbf{x} \\ \vdots \\ \mathbf{y}_8 = (\mathbf{v}_{8,1}, \cdots, \mathbf{v}_{8,n})\mathbf{x} \end{cases}$$

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2. The representation $\mathbf{x}$ and training matrix A remain **invariant**.

References: *Distributed segmentation and classification of human actions using a wearable motion sensor network*. Berkeley Tech Report 2007.

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   - Energy Expenditure: lifestyle-related chronic diseases.

Acknowledgments

Collaborators

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- **Vanderbilt**: Yuan Xue
- **UT-Dallas**: Roozbeh Jafari

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