Ming Hsieh Department of Electrical Engineering

USC Viterbi School of Engineering

Energy-Efficient, Heterogeneous Sensor Selection for Physical Activity Detection in Wireless Body Area Networks

Daphney-Stavroula Zois*, Marco Levorato*,# and Urbashi Mitra*

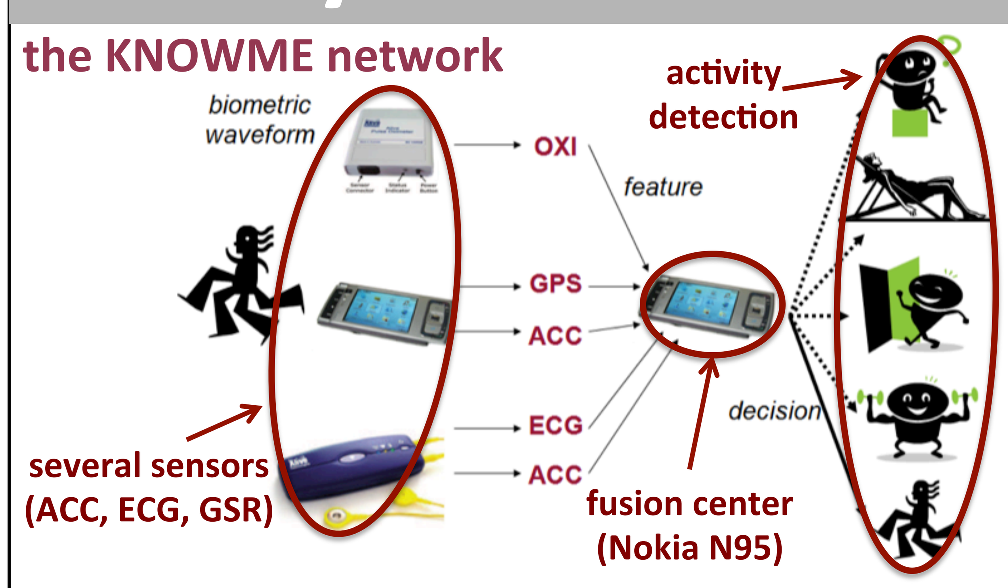
{zois,ubli}@usc.edu, levorato@stanford.edu

Introduction

- Wireless Body Area Networks (WBANs) = sensor networks with,
  - *on-body heterogeneous sensors*
  - *fusion center (a personal device)*
- Biometric sensors: ECG, accelerometers, oxygen, insulin, GSR, etc.
- Applications: health, military, sports, emergency response
- Challenges:
  - (New sensors)
  - Reliability, real-time operation
  - Security, Privacy, User-friendliness
  - POWER CONSERVATION

System Overview & Characteristics

the KNOWME network

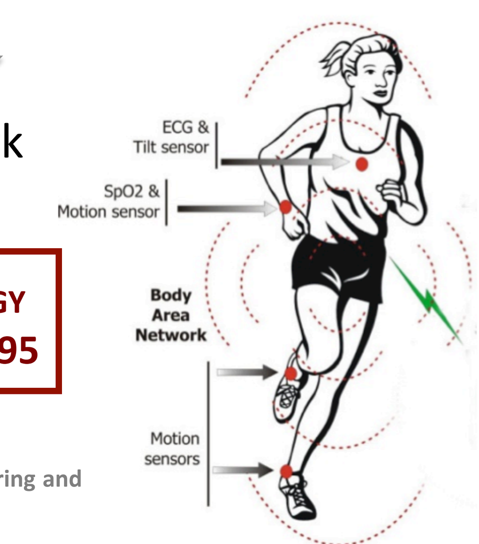


- Wireless communication via Bluetooth

unique constraints

- limited sensor network lifetime

OPTIMIZE ENERGY RESOURCES AT N95



Jovanov et al. Journal of NeuroEngineering and Rehabilitation 2005

- Goal & Approach: energy–efficient activity detection
  - Cheap sensors on phone vs. network sensors (power-saving strategy)
  - Multimodal sensing (different sensor discrimination capabilities)
  - Minimize phone power consumption

- Stochastic dynamical system
- Optimized behavior through sequential decisions

Prior Work

- Typical sensor networks: power minimized at nodes

MDP Framework – select transmission modes / sampling rates / sensor subsets [Chen07, Williams07, Seyedi10]	POMDP Framework – select sensor subsets [Krishnamurthy07, Atia11, Fuemmeler11]	Hierarchical structure / node clustering [Balasubramanian04, Cao05, Dutta05]
	CMDP Framework – select sensor sampling policy [Wang10]	Smart feature Selection + Bayesian statistics [Zappi08, Wang11]

- We cannot use these methods since:
  - Heterogeneous sensors in energy use and detection capabilities
  - Time-evolving physical activity known through noisy observations
  - Constrained energy budget of fusion center (vs. sensors)

Optimization Problem

Cost function $J^{\lambda}=\mathbb{E}\left\{\sum_{k=0}^{L-1} g^{\lambda}(x_k,\mathbf{u}_k)\right\}$

- Total cost: $g^{\lambda}(x_k,\mathbf{u}_k)\doteq(1-\lambda)P_e^{\mathcal{W}}(x_k,\mathbf{u}_k)+\lambda\mathcal{E}(\mathbf{u}_k)$

worst-case error probability

$$P_e^{\mathcal{W}}(x_k,\mathbf{u}_k)\doteq\max_{\substack{x_{k+1},z_{k+1}\\ x_{k+1}\neq z_{k+1}}}[r(x_k,\mathbf{u}_k,x_{k+1},z_{k+1})]$$

normalized energy cost

$$\mathcal{E}(\mathbf{u}_k)\doteq\frac{1}{\mathcal{C}}\sum_{l=1}^{K}N_l^{\mathbf{u}_k}\delta_l$$

different for each sensor

- Partially observable, stochastic control problem

$$\min_{\mathbf{u}_0,\mathbf{u}_1,\ldots,\mathbf{u}_{L-1}} J^{\lambda}$$

Methodology

- Dynamic Programming (DP): $\mathcal{J}_k^{\lambda}(\mathbf{p}_k)=\min_{\mathbf{u}_k\in\mathcal{U}}\left[\mathbf{p}_k^T\mathbf{g}^{\lambda}(\mathbf{u}_k)+\mathcal{A}(\mathbf{p}_k,\mathbf{u}_k)\right]$

$$\mathcal{A}(\mathbf{p}_k,\mathbf{u}_k)=\begin{cases}\sum_{\theta=1}^{n}\mathbb{1}_n^T[\mathbf{P}\circ\mathbf{r}(\mathbf{u}_k,\theta)]^T\mathbf{p}_k\mathcal{J}_{k+1}^{\lambda}\left(\frac{[\mathbf{P}\circ\mathbf{r}(\mathbf{u}_k,\theta)]^T\mathbf{p}_k}{\mathbb{1}_n^T[\mathbf{P}\circ\mathbf{r}(\mathbf{u}_k,\theta)]^T\mathbf{p}_k}\right), & \mathbf{u}_k\neq\mathbf{0}_K^T\\ \mathcal{J}_{k+1}^{\lambda}(\mathbf{P}\mathbf{p}_k), & \mathbf{u}_k=\mathbf{0}_K^T\end{cases}$$

optimal but with high complexity

$$\mathcal{O}(n^3(d+1)^n\alpha L)$$

- Minimum Integrated Cost Time Sharing Sensor Selection (MIC-T3S):
  - Determine solution at corners of belief space via approximate DP
  - Solution at arbitrary belief state determined by time-sharing as

$$\hat{\mathbf{u}}_k^{\mathbf{p}_k}=p_k^1\hat{\mathbf{u}}_k^{\mathbf{s}_1}+\ldots+p_k^n\hat{\mathbf{u}}_k^{\mathbf{s}_n}$$

suboptimal but with lower complexity

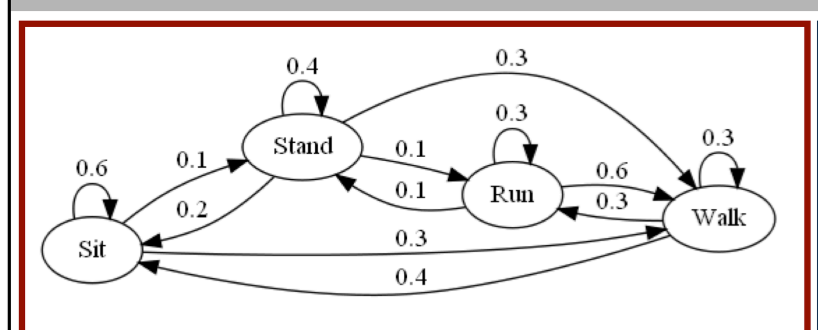
$$\mathcal{O}(n^4\alpha L)$$

$$\hat{x}_k^{\mathrm{ML}}=\arg\max \mathbf{p}_k$$

- Energy-Efficient Maximal Belief Approximate DP (E²MBADP): $\max(\mathbf{p}_k)\geqslant\tau$
- Greedy Minimum Energy & Error Probability Sensor Selection (GME²PS²): $P_e^{\mathcal{W}}(\hat{x}_k^{\mathrm{ML}},\mathbf{u}_k)\leqslant 1-\tau$

control that minimizes instantaneous energy cost

POMDP System Execution



$\mathbf{y}_k=[y_k^1,\ldots,y_k^N]$ with blocks N_1, N_2, N_3, …, N_{K-1}, N_K

AR(1) multivariate Gaussian model

$$H_i^{\mathbf{u}_{k-1}}:\mathbf{y}_k^{\mathbf{u}_{k-1}}\backsim\mathcal{N}(\mathbf{m}_i^{\mathbf{u}_{k-1}},\Sigma_i^{\mathbf{u}_{k-1}}),\ i\in\mathcal{X}$$

interaction between system components

When no samples are selected, no $\mathbf{y}_k$ is generated

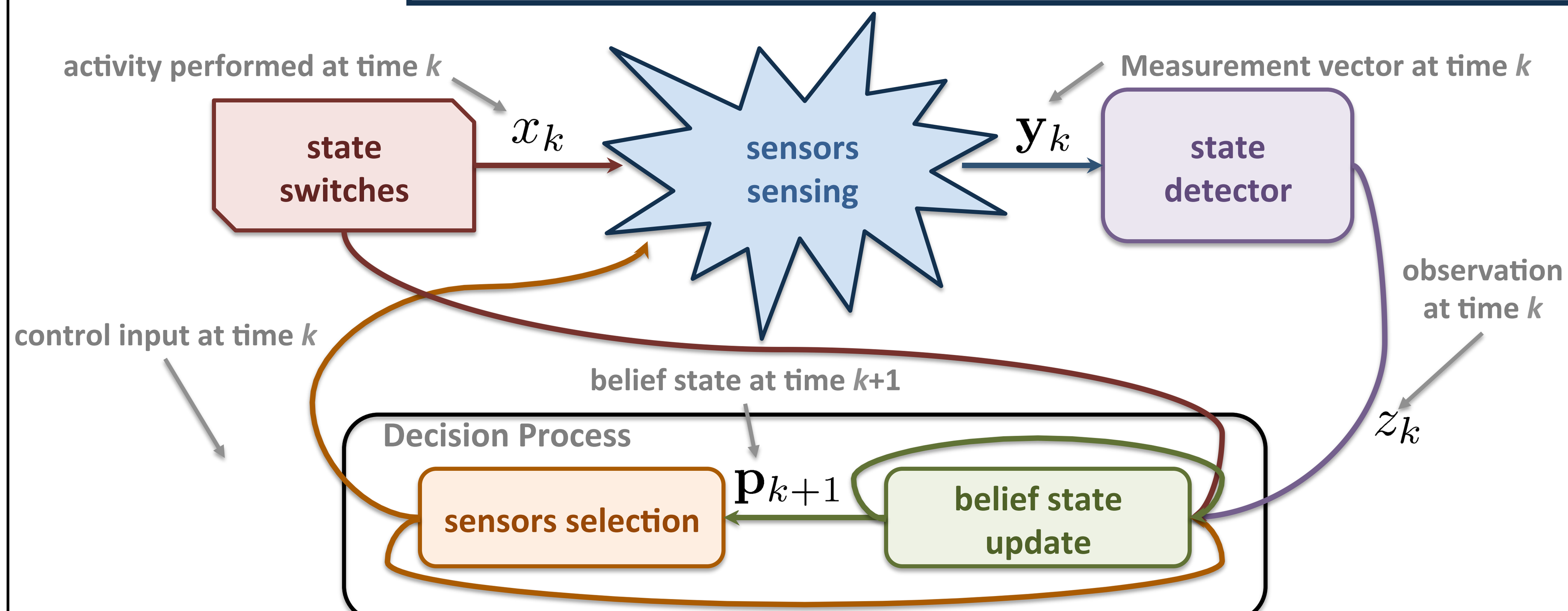
$N_1\times 1$: $\mathbf{m}_i^{\mathbf{u}_{k-1}}=\begin{bmatrix}\mu_{i,S_1}^{\mathbf{u}_{k-1}}\\ \mu_{i,S_2}^{\mathbf{u}_{k-1}}\\ \vdots\\ \mu_{i,S_K}^{\mathbf{u}_{k-1}}\end{bmatrix}$

sensors independent

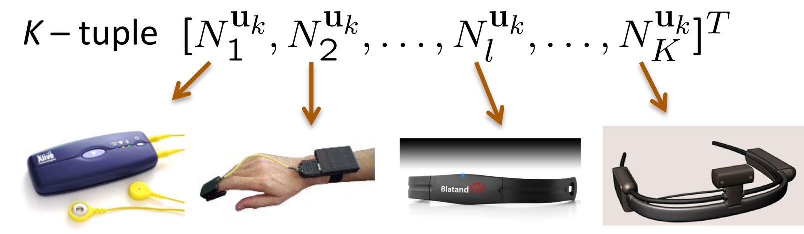
$N_1\times N_1$: $\Sigma_i^{\mathbf{u}_{k-1}}=\begin{bmatrix}\Sigma_i^{\mathbf{u}_{k-1}}(S_1) & 0 & 0 & \cdots & 0\\ 0 & \Sigma_i^{\mathbf{u}_{k-1}}(S_2) & 0 & \cdots & 0\\ 0 & 0 & \Sigma_i^{\mathbf{u}_{k-1}}(S_3) & \cdots & 0\\ \vdots & \vdots & \vdots & \ddots & \vdots\\ 0 & 0 & 0 & \cdots & \Sigma_i^{\mathbf{u}_{k-1}}(S_K)\end{bmatrix}$

block-diagonal

G. Thatte et al., IEEE Transactions on Signal Processing, April 2011



K – tuple $[N_1^{\mathbf{u}_k},N_2^{\mathbf{u}_k},\ldots,N_l^{\mathbf{u}_k},\ldots,N_K^{\mathbf{u}_k}]^T$



$\sum_{l=0}^{K}N_l^{\mathbf{u}_k}\leqslant N$, where N is fixed; # sensors in the network

$\mathbf{p}_k=[p_k^1,p_k^2,\ldots,p_k^n]^T\in\mathcal{P}$ Belief space

- Some samples selected:

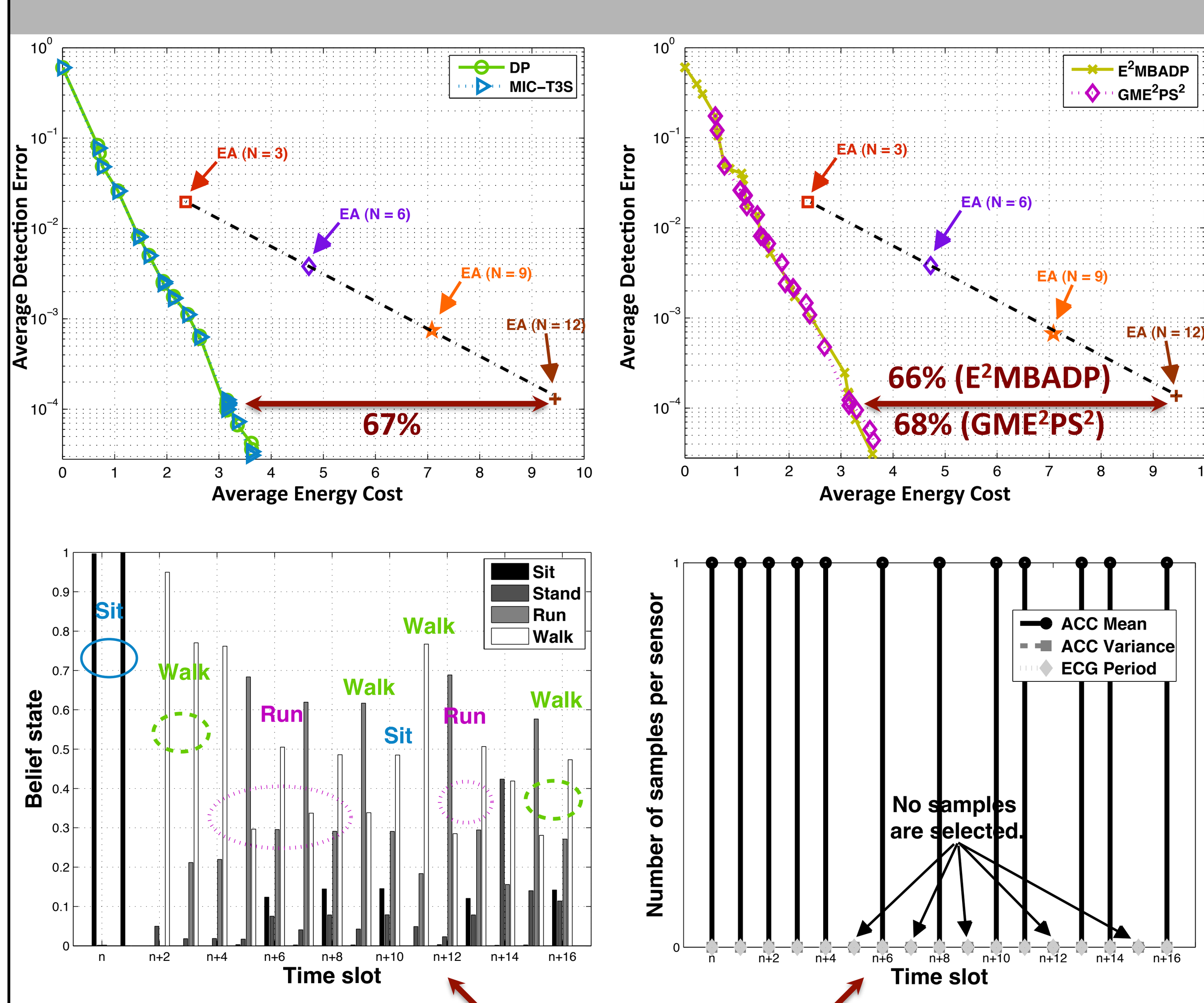
$$\mathbf{p}_{k+1}=\frac{\left[\mathbf{P}\circ\mathbf{r}(\mathbf{u}_k,z_{k+1})\right]^T\mathbf{p}_k}{\mathbb{1}^T\left[\mathbf{P}\circ\mathbf{r}(\mathbf{u}_k,z_{k+1})\right]^T\mathbf{p}_k}$$

- No samples selected:

$$\mathbf{p}_{k+1}=\mathbf{P}\mathbf{p}_k$$

- Estimated activity at time k based on $\mathbf{y}_k$
- Erasure value when no samples selected

Simulations



MIC-T3S performance when more emphasis is on minimizing energy consumption

Framework

- Sensors: {ACC Mean, ACC Variance, ECG Period}
- Activities: {Sit, Stand, Run, Walk}
- Horizon Length L = 5
- $N\in\{3,6,9,12\}$

- Significant energy gains
- Satisfactory detection accuracy
- Few resources utilized

References

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- D.-S. Zois, M. Levorato, and U. Mitra, "A POMDP Framework for Heterogeneous Sensor Selection in Wireless Body Area Networks," INFOCOM Mini-conference 2012.
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*Ming Hsieh Department of Electrical Engineering, University of Southern California, Los Angeles, CA 90089

#Department of Electrical Engineering, Stanford University, Stanford, CA 94305

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