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

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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

System Overview & Characteristics

- 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

Prior Work

- Typical sensor networks: power minimized at nodes

**MDP Framework** – select transmission modes / sampling rates / sensor subsets
- Krishnamurthy07, Atlasi11, Fuenzalida11

**POMDP Framework** – select sensor subsets
- Balasubramanian04, Cadis05, Dutta05

**CMDP Framework** – select sensor sampling policy
- DapsisR10, 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
\[ J = \frac{1}{n} \sum_{i=1}^{n} g(x_i, u_i) \]

Total cost:
\[ g(x_i, u_i) = (1 - \lambda) f(x_i, u_i) + \lambda x_i(u_i) \]

- worst-case error probability
- normalized energy cost

Partially observable, stochastic control problem
\[ \min_{u_0, u_1, \ldots, u_{T-1}} J^\lambda \]

Methodology

- Dynamic Programming (DP):
  \[ J^\lambda(p_k, n_k) = \min_{u_k} \left\{ \frac{1}{T} \sum_{i=1}^{T} g(x_i, u_i) + \lambda x_i(u_i) \right\} \]
  \[ = \min_{u_k} \left\{ \frac{1}{T} \sum_{i=1}^{T} g(x_i, u_i) + \lambda x_i(u_i) \right\} \]

  - Determine solution at corners of belief space via approximate DP
  - Solution at arbitrary belief state determined by time-sharing as
    \[ J^\lambda = \min_{u_k} \left\{ \frac{1}{T} \sum_{i=1}^{T} g(x_i, u_i) + \lambda x_i(u_i) \right\} \]
    suboptimal but with lower complexity

- Energy-Efficient Maximal Belief Approximate DP (EE-MBADP):
  \[ \min_{u_k} \left\{ \frac{1}{T} \sum_{i=1}^{T} g(x_i, u_i) + \lambda x_i(u_i) \right\} \]
  \[ = \min_{u_k} \left\{ \frac{1}{T} \sum_{i=1}^{T} g(x_i, u_i) + \lambda x_i(u_i) \right\} \]

Simulations

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

References


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