
Farshid Hassani Bijarbooneh    Wei Du
Edith Ngai    Xiaoming Fu

ASTRA and Mobility Research Groups
Department of Information Technology
Uppsala University, Sweden
http://www.it.uu.se/research/group/astra
http://www.it.uu.se/research/group/core

Research Unit in Networking (RUN),
University of Liège, Belgium
http://www.run.montefiore.ulg.ac.be

Institute of Computer Science,
University of Göttingen, Germany
http://www.uni-goettingen.de

IWQoS’14, International Symposium on Quality of Service.
Hong Kong, May 26 – 28, 2014
Motivation and Goal

Collect high quality data efficiently using sensor nodes:
- Increase network life-time and energy-efficiency
- Energy load balancing
- Consider link quality and routing
- Exploit spatio-temporal correlation
Contributions and Highlights

- Introducing adaptive sensing with belief propagation (ASBP) protocol.

- The formulation of the active sensor selection optimisation problem.

- Construct a graph model for WSN with spatio-temporal data correlation to be used by belief propagation.

- The effect of data quantisation on the data correlation.
Adaptive Sensing with Belief Propagation (ASBP) protocol

- Conserve energy by predicting missing data and using links with better quality.

- Objective:
  - Maximise the link quality of the multi-hop path to the sink.
  - Select a set of active sensors for data collection.
  - Minimise the correlation of the data between the active sensors.
Adaptive Sensing with Belief Propagation (ASBP) protocol (continued)

ASBP has two phases:

- **Phase 1**: All sensors collect data in the sensing field.
  - Only 20 readings are required.
  - Link quality is estimated.
  - Correlation coefficient matrix is constructed.
  - Select a set of active sensors by solving an optimisation problem.

- **Phase 2**: Sensing phase.
  - Only the active sensors are sensing and transmitting data.
  - Base station uses belief propagation (BP) to reconstruct the missing data.
Model

- Decision variables:
  \[ x[s] \in \{0, 1\}, \]
  1 if sensor \( s \) is selected, 0 otherwise \( s \in S \)

- Objective function:
  \[
  \text{maximise} \sum_{s \in S} E[s]^\alpha \cdot u[s]
  \]

- \( S \): Set of all sensor nodes.
- \( \alpha \): Weight Constant (typically 0.5).
- \( E \): Residual energy.
- \( u[s] \): Data utility of the sensor \( s \).
Model - Constraints

- Data utility constraints, \( \forall s \in S \):
  \[
  u[s] = w_1 \cdot x[s] \cdot q[s] - w_2 \cdot \sum_{s' \in S, \ s' \neq s} x[s] \cdot x[s'] \cdot C[s, s']
  \]

- Routing constraints, \( \forall s \in S \):
  \[
  q[s] = \max_{p \in P[s]} \left( B[n_p] \cdot \prod_{(s', s'') \in p} (x[s''] \cdot L[s', s'']) \right)
  \]

- Path quality constraints:
  \[
  \forall s \in S, \quad q[s] \geq x[s] \cdot t
  \]

- Active sensor constraints:
  \[
  \sum_{s \in S} x[s] \geq m
  \]
Implied Constraints

\[ p_1 : \langle (1, 5), (5, 6), (6, 4) \rangle \]
\[ p_2 : \langle (1, 2), (2, 3), (3, 4) \rangle \]

**Intersection of paths between two end-points:**

\[ \forall s \in S \ (x[s] = 1) \implies \left( \bigwedge_{s' \in P \cap [s]} x[s'] \right) = 1 \]
Routing Constraint - Example

$p_1 : \langle (1, 5), (5, 6), (6, 4) \rangle$

$p_2 : \langle (1, 2), (2, 3), (3, 4) \rangle$

$q_{p_1}[1] = L[1, 5] \cdot L[5, 6] \cdot L[6, 4] \cdot B[4] = 0.406$

$q_{p_2}[1] = L[1, 5] \cdot L[5, 6] \cdot L[6, 4] \cdot B[4] = 0.387$

$q[1] = \max(x[5] \cdot x[6] \cdot x[4] \cdot q_{p_1}[1], x[2] \cdot x[3] \cdot x[4] \cdot q_{p_2}[1])$

- Routing constraints, $\forall s \in S$:

$$q[s] = \max_{p \in P[s]} \left( B[n_p] \cdot \prod_{(s', s'') \in p} (x[s''] \cdot L[s', s'']) \right)$$
Belief Propagation (BP)

- BP is a classic algorithm for performing inference on graphical models, Yedida et al. [YFW03]

- Infers the underlying event from the observations.
Belief Propagation (BP)

- BP is a classic algorithm for performing inference on graphical models, Yedida et al. [YFW03]
  - Infers the underlying event from the observations.
Instance Data

- Real data from Intel Berkeley Research Lab.
- 54 sensor nodes.
  - Temperature, light intensity, humidity, and voltage.
  - Link quality estimations.
Results: Correlation and Quantisation
Results: Correlation and Quantisation

![Graph showing correlation mean square error (percentage) against number of quantisation bits. The error decreases significantly as the number of quantisation bits increases from 3 to 14.]
Results: Data Utility

The optimum balance between link quality and correlation is achieved by selecting 25 active sensor nodes of 54.

(a) Minimum 30% base station link quality

(b) Minimum 70% base station link quality
Results: Energy Consumption

- Save up to 80% energy by selecting only 10 active sensor nodes in each round.

(a) Minimum 30% base station link quality
(b) Minimum 70% base station link quality
Belief Propagation Prediction Error

- BP with only 10 active sensor nodes achieves an error prediction of 6%.
- Standard deviation of the error for 10 sensors is only 12%.
Summary and Conclusion

- Effective to use constraint programming (CP).
- Proof of optimality with CP and good quality local optimum with greedy.
- ASBP works best for environment with spatio-temporal correlation in data.
- ASBP saves up to 80% energy while maintaining load balancing.
- BP predicts the missing data *iteratively* as the stream of data is received.
- Collaborative sensing with mobiles and wireless sensors can provide high sensing quality with reduced deployment cost.
Future Work

- Distributed implementation for real deployment.
- Integrate adaptive sampling rate into ASBP.
- Multi-sink scenarios including mobile sinks.
This research is in part sponsored by the Swedish Foundation for Strategic Research (SSF) under research grant RIT08-0065 for the project *ProFuN: A Programming Platform for Future Wireless Sensor Networks*, and sponsored by the U4 Strategic University Network DAAD Programme ÒStrategic Partnership and Thematic NetworksÓ.
Questions

- Thank you!
- Questions:
  - farshid.hassani@it.uu.se