Low Power Wireless Sensor Networks

Siamak Aram
DAUIN
Department of Control and Computer Engineering
Politecnico di Torino
Ph.D. Dissertation

Advisor: Prof. Eros Pasero

February 27th, 2015
DET – Neuronica LAB

The Communication and Signal Processing Laboratory

The Informatics Systems and Applications Group
Department of Mechanical Engineering,
Aristotle University of Thessaloniki (AUTH)
Taxonomy of approaches to energy savings in sensor networks (1)
Communication component of a sensor consumes more power than the computational unit. That power consumption is minimum in the sleep state of the radio communication. The rationale behind the method implies that sensors could be powered down in judiciously chosen time intervals to read required data. The correlation among the points would allow prediction of sensed data during sensors' idle periods.

The microcontroller can switch on the sensors only during the measurement, reducing the power consumption. Nevertheless, unneeded communications could sporadically happen because of transferring unnecessary data. Reducing extra communications is a way to save energy which can be followed by data driven techniques.

Taxonomy of approaches to energy savings in sensor networks (2)

- Duty Cycling
- Data Driven
- Mobility-Based

Combination of the approaches
Environmental Sensing using Smartphone [1,2,3]

Duty Cycling

Smartphones
Capabilities
Sensing features
Communication features

Bluetooth
Power: 0.6mW sleep mode and 90mW during transmission

Sensor
SHT11
Accuracy: 0.4% C and 3%
Power: 80µW

This work was sponsored by:
• National projects AWIS (Airport Winter Information System)
• ITACA (Innovazione Tecnologica, Automazione e nuovi Controlli Analitici per migliorare la qualità e la sicurezza dei prodotti alimentari piemontesi)
• Both funded by Piedmont Authority, Italy, and by the private company Reply
Low Power Acquisition System

- Application Improvement
  - aBlueSen
  - Tokenizing
  - Buffer Size
  - Automatically communicating

- Sensor Structure
  - SHT21 with higher accuracy; 0.3% C and 2%

- 4 Months
  - Reducing Power Consumption
  - Increasing number of Sensors

- Duty Cycling

- Data Set

- Sensor Itself

- Bluetooth

- Power Consumption:
  - Bluetooth: 90mW
  - 26mW
  - 3mW
  - 24µW
Neural Data Driven approach (1) [4,5,6]

Data Prediction – Data Reduction Algorithm

Forward prediction by periodically using MLP
Prediction computed as mean of 100 estimations

Uncertainty of prediction \( (U) \) = Dispersion of prediction \( (U_1) \) + Prediction error \( (U_2) \)

Each available measurement with its uncertainty assumed to be equal sensor accuracy

An additional measurement when uncertainty > selectable threshold

Predicted and estimated uncertainty of prediction

Neural Data Driven approach (1) [4,5,6]
Experimental Data (1)
Meteorological data of Turin Caselle Airport for 100 days

Experimental Data (2)
Indoor environmental information with three different locations in Neuronica LAB

Simulated Data (1)
Two Signals
Deterministic
Noise Free
Quantization Resolution: 0.05

Simulated Data (2)
Two Signals
Uncorrelated
Sinusoid and Lorenz System
Result – First Approach

(C) Representative example application for the method.
Result – First Approach

Application of the algorithm to simulated data

(A) Number of samples and mean estimation error (mean and standard deviation over ten repetitions). (B) Representative example (threshold = 0.03 for both signals).
Result – First Approach

Application of the algorithm to meteorological experiments

Accuracy is assumed to be 0.2°C, 20 hPa, 0.1 km/h, and 1%, for the temperature, pressure, wind velocity, and humidity sensors, respectively. (A) Root mean square estimation error and reduction ratio as functions of the uncertainty threshold (20 repetitions are considered). (B) Example of application to a portion of the test set.
Neural Data Driven approach (2) [7]

Time Series Data Prediction – Data Reduction

Algorithm

01. Training Algorithm
   The Levenberg-Marquardt (LM) algorithm as the training algorithm of the classifier

02. Regularization
   Every iteration, regularized cost for the training data is calculated
   \[ J(\beta) = \frac{1}{m} \sum_{i=1}^{m} y^i \log(P(x^i)) + (1 - y^i) \log(1 - P(x^i)) + \frac{\lambda}{2m} \sum_{j=1}^{n} \beta_j^2 \]

03. Two Delayed feedback
   The network uses the temperature values at two delayed time-stamps to predict the current value
   \[ y(t) = F[y(t-1), y(t-2), \ldots, y(t-d)] \]

04. One Hidden Layer
   For the hidden layer, sigmoid activation function is used whereas linear function is applied at output neuron.

05. Stopping Training
   Training is set to be stopped if either there are six consecutive increasing in validation error or the gradient becomes less than the selected threshold

06. Artificial NN for Time Series Prediction
   We used an Artificial Neural Network (ANN) by employing NAR model for time series prediction

07. Optimizing Neurons and Performance

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum gradient threshold</td>
<td>$1 \times 10^{-4}$</td>
</tr>
<tr>
<td>Initial learning rate ($\mu$)</td>
<td>0.01</td>
</tr>
<tr>
<td>Increasing ratio of $\mu$</td>
<td>10</td>
</tr>
<tr>
<td>Decreasing ratio of $\mu$</td>
<td>0.1</td>
</tr>
<tr>
<td>Maximum value for $\mu$</td>
<td>$1 \times 8$</td>
</tr>
</tbody>
</table>
Neural Data Driven approach (2)

Time Series Data Prediction – Data Reduction

Block Diagram of overall Methodology
Result – Second Approach

Time series prediction response of the neural network with the error by varying the size of hidden layer of the network.

Mean Squared Error plot for each of the sensor's data against different number of hidden layer neurons used in the network.
Result
Second Approach

Network prediction response with 20 hidden neurons by varying the number of inputs, Temperature sensor 1, dataset 1

Mean Squared Error plot for each of the sensor’s data against different number delayed outcomes used as input to the network

MAPE plot for each of the sensor’s data against different number of network inputs
NAR was selected which performs time series prediction by using the target values at subsequent delayed time stamps as inputs, and predicts the value at the current time stamp.

Performance
Based on MSE with the aforementioned data to estimate a good network architecture with optimum choice of hidden layer neurons.

Optimization
By optimizing number of neurons and network size

Low error percentage
By optimizing system specially hidden layer neurons
Overview of the Works

In each step we achieved greater reduction of communication and, subsequently, lower power consumption at small error rate.
**Communication**

While 33.3% is the prediction time, it is possible to reduce the communication time.

**Error margin - Temperature**

75% power can be saved within an error margin 2.6% by network + 1% of the sensor.

**Error margin – Humidity**

66% power can be saved within an error margin 2.2% by network + 1% of the sensor.
Extra Activities
In AuTh, HU and Polito

- **POLITO Representative**
  - 2012-2014

- **Assistantship**
  - Howard university

- **Reviewing Journal Paper**
  - Two Journals

- **Co-Adviser**
  - Undergraduate students’ thesis

- **Collaboration**
  - POLITO and HU
Publications


