Reducing The Data Transmission in Wireless Sensor Networks Using The Principal Component Analysis

A. Rooshenas, H. R. Rabiee, A. Movaghar, M. Y. Naderi

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Problem Definition

Different Power Consumption in Routing Tree

- Leaf Nodes
- Intermediate Node

Problems

- Intermediate nodes should relay other packets to the base station.
- Lifetime of intermediate nodes affect the longevity of Wireless Sensor Networks
Dimension Reduction

\[ X_2 \]

\[ X_1 \]

\[ v \]
Dimension Reduction

\[ y = v^T x \]
Dimension Reduction

\[ y = \mathbf{v}^T \mathbf{x} \]

\[ \hat{\mathbf{x}} = \mathbf{v} \mathbf{y} \]
Related Works

- Principal Component Aggregation (PCAg).
  - Unsupervised
  - Supervised

- Distributed Principal Component Analysis (DPCA).
Principal Component Aggregation

- Base station gathers observations from sensor networks
Principal Component Aggregation

- Base station calculates eigenvectors and sends them back to network
Sensor nodes send partial PCs in each epoch
The base station reconstructs observations
Reconstruction error is not available at the base station
The base station calculates eigenvectors periodically
The base station sends PCs to the network

Each sensor can calculate its reconstruction error

\[ e_i = \| x_i - y \times v_i \| \]

Updating one observation may change all other elements of an eigenvector

Update decision is ambiguous
Assumptions:
- Each sensor receives sensed value from its neighbors
- Only the data of sensors which are in the radio range of each other are correlated

For the computation of eigenvectors, DPCA uses:
\[ v_{i}^{t+1} = \sum_{j=1}^{N} C_{ij} \cdot v_{j}^{t} \]

- Each sensor broadcasts its eigenvector’s entry \( v_{i} \) and its sensed value.
- Assumptions of DCPA are not supported by weather data
Using PCA for Data Reduction

Retained Variance for 50 sensors

<table>
<thead>
<tr>
<th></th>
<th>Retained Variance</th>
<th>$\lambda_1/\lambda_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temperature</td>
<td>1.0</td>
<td>3.6909e+015</td>
</tr>
<tr>
<td>Humidity</td>
<td>1.0</td>
<td>3.4407e+015</td>
</tr>
<tr>
<td>Light</td>
<td>1.0</td>
<td>2.4402e+015</td>
</tr>
<tr>
<td>Voltage</td>
<td>1.0</td>
<td>3.1737e+015</td>
</tr>
<tr>
<td>Combined</td>
<td>1.0</td>
<td>1.9305e+015</td>
</tr>
</tbody>
</table>
Leaf nodes send their observations
Intermediate nodes compute PCs
Intermediate nodes recalculate PCs according to reconstruction error
The next level intermediate nodes reconstruct observation and compute PCs from all downstream observations
The base station reconstructs observations

\[ y = f(x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8) \]
\[ y_1 = f(x_1, x_2, x_5) \]
\[ y_2 = f(x_3, x_4, x_7) \]
Updating Eigenvectors

- Eigenvectors are common between each pair of parent-child intermediate nodes.
- Nodes which are in the vicinity of the base station must send large eigenvectors.
- For these nodes, the computation of the covariance matrix and eigenvectors is energy consuming.
- Updated eigenvectors must be sent to the base station.
- The base station calculates final eigenvectors.
Features of Using PCA

- Each intermediate node has error threshold that can be configured by the base station
- High threshold value causes low accuracy and high efficiency
- An intermediate node only sends PCs in each epoch
Collective PCA

- Reconstruction of data in each intermediate node and combination again is not scalable
- Collective PCA: PCA is invariant to an orthonormal linear transformation
- We want to find the principal component of $\mathbf{x} = [\mathbf{x}_1^T, \mathbf{x}_2^T, s]^T$ where $s$ is sensed value.
- $y_1$ and $y_2$ are principal components of $\mathbf{x}_1$ and $\mathbf{x}_2$
- $\mathbf{z} = \begin{bmatrix} y_1 \\ y_2 \\ s \end{bmatrix}$ and $\mathbf{g}$ is the eigenvector of $\mathbf{z}\mathbf{z}^T$ then the principal component of $\mathbf{x}$ is $\mathbf{y} = \mathbf{g}^T\mathbf{z}$
Aggregation of PCs using Collective PCA

- Leaf nodes send their observations
- Intermediate nodes compute PCs
- The next level intermediate nodes compute PCs from observations and received PCs
- The base station reconstructs observations
- Intermediate nodes only send PCs in each epoch

\[ y_1 = f(x_1, x_2, x_5) \]

\[ y_2 = f(x_3, x_4, x_7) \]

\[ x_6 \]

\[ y = f(y_1, y_2, x_6, x_8) \]

\[ \hat{x} = g(y) \]
Updating Eigenvectors

- Each intermediate node has its eigenvectors
- Each intermediate node updates its eigenvectors independently
- Updated eigenvectors must be sent to the base station
- The base station calculates final eigenvectors
- Update rate depends on the number of changes in environment

\[ g = [g_8(1) \ast g_5^T, g_8(2) \ast g_7^T, g_8(3), g_8(4)]^T \]
Proposed method: An aggregation service for calculation of reconstruction Error

- In PCAg, the base station needs to update eigenvectors in order to compute reconstruction error.
- In LocalPCA, the base station needs to tune thresholds.
- In PCAg and LocalPCA, the base station do not access the real observation to calculate reconstruction error.
- We proposed an aggregation service facilitating the calculation of reconstruction error at the base station.
- EAPCAg: We enhance PCAg using this aggregation service.
Proposed method: An aggregation Service for Calculation of Reconstruction Error

\[
\| \hat{x} - x \|^2 = (\hat{x} - x)^T (\hat{x} - x)
\]

\[
= \hat{x}^T \hat{x} - \hat{x}^T x - x^T \hat{x} + x^T x
\]

\[
= x^T A A^T x - 2x^T A A^T x + x^T x
\]

\[
= x^T x - x^T A A^T x
\]

\[
= x^T x - y^T y
\]

\[
= \sum_{i=1}^{n} x_i^2 - \sum_{i=1}^{p} y_i^2 \quad p \ll n
\]
Data Set

7500 epoch of 10 sensors from Intel-lab

Temperature (°C)
Simulation Scenario

Outline
- Introduction and Related Works
- Proposed Method
- Simulation
- Conclusion

Settings

Results

Simulation Scenario

Base Station

Nodes 9, 10, 1, 2, 3, 4, 5, 6, 7, 8, 21, 22, 23, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20

Reducing The Data Trans. in WSN using PCA

DML 8 Dec 2010 Amirmohammad Rooshenas

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### Packet Size

<table>
<thead>
<tr>
<th>Field</th>
<th>Size</th>
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<tbody>
<tr>
<td>Header</td>
<td>10</td>
</tr>
<tr>
<td>Observation</td>
<td>2</td>
</tr>
<tr>
<td>Eigenvector element</td>
<td>4</td>
</tr>
<tr>
<td>Principal Component</td>
<td>4</td>
</tr>
<tr>
<td>Squared observation</td>
<td>4</td>
</tr>
<tr>
<td>Request for observation</td>
<td>1</td>
</tr>
</tbody>
</table>
## Numerical Results

<table>
<thead>
<tr>
<th></th>
<th>Transmitted Bytes</th>
<th>Error Mean</th>
<th>Error Variance</th>
<th>Error Max</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>PCAg</td>
<td>200340</td>
<td>0.82</td>
<td>0.96</td>
<td>8.34</td>
<td>update: 11 epoch</td>
</tr>
<tr>
<td>LocalPCA</td>
<td>168114</td>
<td>0.82</td>
<td>0.07</td>
<td>1.43</td>
<td>threshold at 23:1.0</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>threshold at 22,21: 0.35</td>
</tr>
<tr>
<td>EAPCAg</td>
<td>215216</td>
<td>0.82</td>
<td>0.23</td>
<td>6.16</td>
<td>threshold:1.42</td>
</tr>
</tbody>
</table>
For the sensor node 23rd, EAPCAg method has sent about 15K bytes more than PCAg algorithm.

PCAg method has sent about 32K bytes more than LocalPCA.

The average updating interval in EAPCAg is about 13.84 epochs which is around 3 epochs more than PCAg.

EAPCAg has less efficiency than PCAg because the size of each PC packet is increased from 14 bytes to 18 bytes.

In PCAg and EAPCAg methods, when the number of sensor nodes increases, the eigenvector packets should be divided to smaller packets, so the amount of transmitted data will increase.
Comparision of LocalPCA with PCAg at the Base Station
Error of LocalPCA

![Error of LocalPCA Chart](chart.png)
Error of PCAg

Error of EAPCAg

Epochs
Future Works

**PCA**

- Efficiency of LocalPCA depends on thresholds
- Thresholds should be adjusted adaptively
- Weather data has low dimensions. LocalPCA will show better performance with high dimensional data (e.g. image)
- Kernel PCA is an non-linear version of PCA and can handle data which changes rapidly


Y. L. Borgne and G. Bontempi. Unsupervised and supervised compression with principal component analysis in wireless sensor networks. in Proc. First International Workshop on Knowledge Discovery from Sensor Data, 13th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2007
Questions?
How to find eigenvectors

- Computation of Covariance Matrix
  \[ \Sigma = E[(x - E[x])(x - E[x])^T] \]

- Solve eigenvector, eigenvalue equation \( \Sigma \alpha = \lambda \alpha \)

- If \( \lambda_i \) is largest eigenvalue and \( \Sigma \alpha_i = \lambda_i \alpha_i \)
  then \( \alpha_i \) is dominant eigenvector.

- When the dimension reduction from \( n \) dimension to \( q \) dimension is efficient?

- Retained Variance: \( H(q) = \frac{\sum_{k=1}^{q} \lambda_k}{\sum_{k=1}^{n} \lambda_k} \)
Power Iteration Method

- Calculation of eigenvectors by eigenvector, eigenvalue equations is time consuming $O(n^3)$.
- Power Iteration Method approaches to dominant eigenvector very fast $O(n^2)$.
- PIM iteration: $g^{k+1} = \Sigma g^k$
- FastPCA : Extension of PIM for calculation of other eigenvectors.