TerraSwarm

Managing energy and data quality in large sensor swarms

Energy efficiency vs. data quality

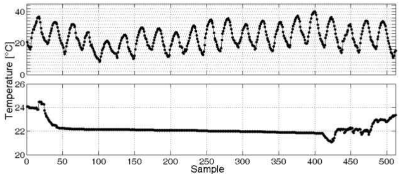
http://terraswarm.org/

Jinseok Yang, Sameer Tilak, Tajana Simunic Rosing (UCSD)

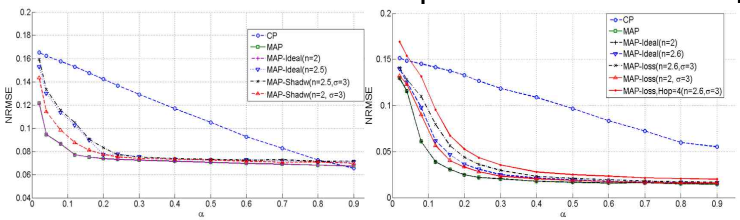
Reducing the total number of samples collected by heterogeneous sensors

- Reconstruct missing data a latent factorization model for multivariate spatio-temporal data

Comparison of the temperature signal collected from different outdoor (top) and indoor (down) networks

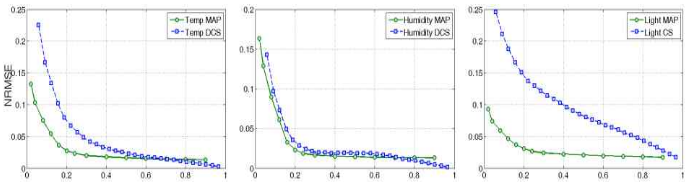


Reconstruction error comparison



- Our technique (MAP) vs. standard tensor factorization (CP)
- MAP reconstruction error below 9%, with up to 80% of the missing samples under the worst wireless channel condition

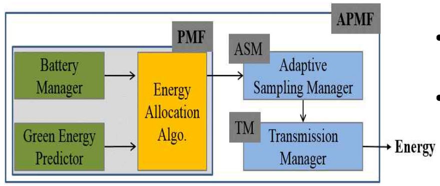
Comparison with distributed compressive sensing(DCS)



Temperature Humidity Light

- MAP performs better when a smaller portion of data is collected
- Temperature has 6% lower normalized root mean square error (NRMSE) with only 20% of data collected
- Light samples have >10% lower NRMSE with 20% of data

Integrated energy efficiency



- Adaptive Power Management Frameworks (APMF) combines adaptive sampling and transmission with energy level based power manager (PMF)
- Adjusts sampling rate based on measurement characteristic.
- Optimal data transmit time decided based on energy and delay tradeoff

Relative energy in comparison with PMF using buoy data

vs. PMF	Humidity	Temperature
APMF	27%	32%
APMF w/o TM	62%	72%
APMF w/o ASM (5min)	48%	53%
APMF w/o ASM (10min)	46%	42%

APMF results in 28% to 73% energy saving vs. PMF
Transmission module(TPM) is dominating factors for energy saving

Estimation error in comparison with PMF using buoy data

vs. PMF	Humidity	Temperature
APMF	1.5%	0.5%
APMF w/o TM	1.2%	0.3%
APMF w/o ASM (5min)	0.9%	0.3%
APMF w/o ASM (10min)	1.3%	0.5%

- Measured temperature and humidity are slowly varying , at most 4.2°C and 4.5% variance respectively per day

Relative energy consumption with a fast varying lake data set

	Energy consmp. (%)
APMF	62%
APMF w/o TM	88%
APMF w/o ASM (5min)	74%
APMF w/o ASM (10min)	69%

- Level of chloride has large variations per day ~3000(mg/L) → lower energy savings than slow varying measurements

Adapt broadcasting rate based on user's mobility

- Smart cities provide data to users
- Users register to receive the data from sensors of interest

- Sensor nodes adjust their broadcasting rate as a function of the number of users and their speed (m/s)

Steady congested and non-congested traffic

Traffic type	Mean(*m/s*)	Stdv (*m/s*)	Density (ped/m^2)	Flow level (ped/s)
Non-congested	1.46	0.15	0.2	0.2
Congested	0.96	0.26	0.8	1.2

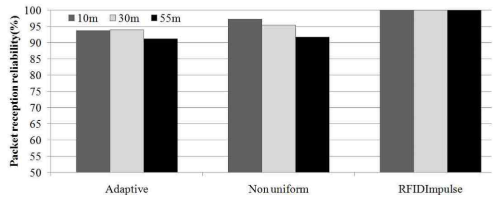
- Behavior of masses of people is modeled similar to gases
- Congestion increases density and decreases the mean speed

Factor reduction in energy consumption [# messages]

TxRange/ Protocol	Adaptive	Non-uniform[14]	Periodic	RFIDImpulse [3]
10m	10.83 [21]	6.31 [41]	6.31 [41]	1.29 [100]
30m	23.97 [11]	12.06 [17]	12.06 [17]	1.12 [100]
55m	33.65 [6]	13.05 [12]	13.05 [12]	1 [100]

- Query based approach (RFIDImpulse) does not adjust the broadcast rate as a function of users' mobility
- As Tx range increases, the overall energy consumption decreases

Reliability comparison



- 90% of users can receive the data from sensors
- Our design is as reliable as the other protocols (only 2% difference)

Publications

[1] B. Milosevic et. al, "Efficient Energy Management and Data Recovery in Sensor Networks using Latent Variables Based Tensor Factorization" IEEE/ACM MsWiM 2013
[2] JS. Yang et. al, "Leveraging application context and detailed battery model for efficient sensing", submitted to DATE 2014
[3] JS. Yang et. al, "A novel protocol for adaptive broadcasting of sensor data in urban scenarios", IEEE GlobeCom, 2013

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