Edge Mining the Internet of Things

Elena I. Gaura, *Member, IEEE*, James Brusey, *Member, IEEE*, Michael Allen, Ross Wilkins, Dan Goldsmith, and Ramona Rednic

What is Edge Mining?

- Processing of sensory data near or at the point at which it is sensed
- In order to convert it from a raw signal to contextually relevant information
- To reduce energy usage, remote storage requirement and risk in personal privacy.

Why Edge Mining

- Many IoT scenarios are based on Wireless Sensor Networks (WSN).
- Devices that are used to sense and send data wirelessly are resource constrained.
- Connections of the devices are bandwidth limited.

- Cost energy, infrastructure, communication, storage
- Analytics automatic interpretation

The Idea of Edge Mining

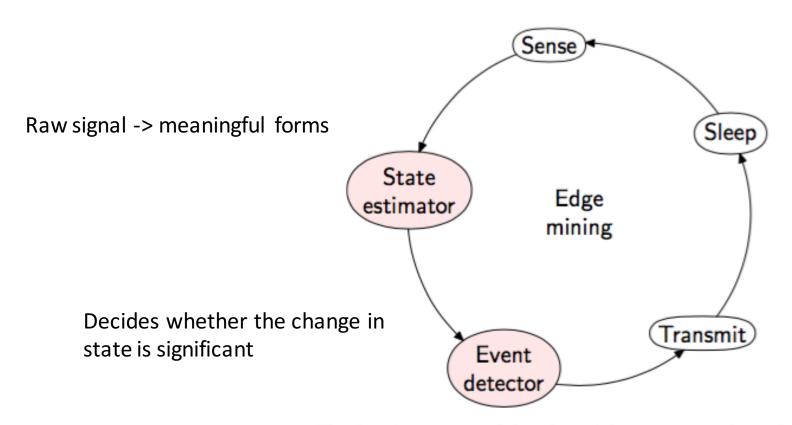


Fig. 1. A summary of the edge mining process at the node.

Three Edge Mining Algorithms

- L-SIP, Linear Spanish Inquisition Protocol
- ClassAct
- BN, Bare Necessities

- Reducing sensing messages
- Conceptually simple to implement
- Based on a general edge mining algorithm, G-SIP

Efficient Energy Resource Utilization

- Traditionally, the focus is exploiting internode communication, innetwork intelligence building, hardware optimization and energy management.
- However, collaborative WSNs are unusual in real-life systems.

- Central to the concept of edge mining:
 - The better the information requirements of a given application are understood, the greater the potential to reduce the raw signal
 - Saving packets rather than bits

General SIP (Spanish Inquisition Protocol)

A node only transmits that which the receiver does not expect.

Algorithm 1 General Spanish Inquisition Protocol (G-SIP) (node algorithm). Note that this is a generalised form of the previously published SIP algorithm [3]

- 1) **z** ← obtain vector of sensor readings
- 2) $t \leftarrow \text{current time}$
- 3) $\mathbf{x}_{\text{new}} \leftarrow \text{estimate new state}(\mathbf{z}, \mathbf{x}_{\text{old}}, t_{\text{old}})$
- 4) $\mathbf{y}_s \leftarrow \text{predict sink state}(\mathbf{y}_{\text{sink}}, t_{\text{sink}}, t)$
- 5) $\mathbf{y}_{\text{new}} \leftarrow \text{simplify}(\mathbf{x}_{\text{new}})$
- 6) if eventful $(\mathbf{y}_{\text{new}}, \mathbf{y}_s)$ or $t t_{\text{sink}} \ge t_{\text{heartbeat}}$ (if the state is eventful or if time since the last transmission exceeds a threshold)
 - a) transmit $(\mathbf{y}_{\text{new}}, n, t)$
 - b) $n \leftarrow n + 1$ (increment sequence number)
 - c) when acknowledgement received:
 - i) $\mathbf{y}_{\text{sink}} \leftarrow \mathbf{y}_{\text{new}}$
 - ii) $t_{\text{sink}} \leftarrow t$
- 7) $\mathbf{x}_{\text{old}} \leftarrow \mathbf{x}_{\text{new}}$
- 8) $t_{\text{old}} \leftarrow t$

Linear SIP

• It encodes the state as a point in time value and rate of change $\mathbf{x} =$

(X,X')T

Algorithm 2 Linear SIP (L-SIP) phrased in terms of G-SIP in Algorithm 1

estimate new state

dEWMA filtering:

$$x_1' \leftarrow \alpha z + (1 - \alpha) (x_1 + x_2 \Delta t)$$

$$x_2' \leftarrow \beta (x_1' - x_1) / \Delta t + (1 - \beta) x_2$$

(Update filtered estimates of value x_1 and rate of change x_2 . Δt denotes the time interval between samples.)

predict sink state

$$\mathbf{y}' \leftarrow \begin{pmatrix} 1 & t - t_{\text{sink}} \\ 0 & 1 \end{pmatrix} \mathbf{y}_{\text{sink}}$$
 (linear extrapolation)

simplify

 $y \leftarrow x$ (no simplification)

eventful?

yes if
$$|y_1' - y_1| > \varepsilon$$

(The measurement is eventful if the value estimate y_1 differs from the prediction y'_1 by at least some threshold ε .)

Evaluation of L-SIP

- Message Reduction
- Energy Reduction
- Network and Database Effects

 L-SIP is useful for data transmission reduction where the application requires that the raw data stream be reconstructable in the future. (e.g., environment sensors, at low frequency)

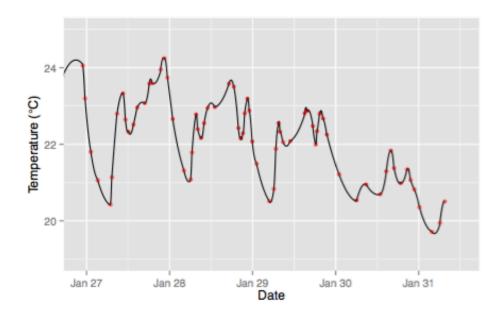


Fig. 2. Example reconstructed temperature time series based on L-SIP with a threshold of 0.5 °C. Signal reconstructed with 68 L-SIP packets instead of 1189 raw data packets (6%). Circles are used to mark when transmissions occurred. This graph is derived from a deployed house monitoring system that uses L-SIP.

TABLE III

MICRO-BENCHMARK ESTIMATES FOR USING L-SIP ON TELOSB FOR VARIOUS LISTENING OPTIONS. THE ESTIMATE FOR TSMP IS BASED ON REPORTED DUTY CYCLES OF 0.1%. THE ENERGY USE IS RELATIVE TO THE ESTIMATED USE FOR LPL WITHOUT L-SIP AS SHOWN IN TABLE II

	Energy use relative to LPL
LPL + L-SIP 5%	79%
TSMP 0.1% + L-SIP 5%	27%
No listening + L-SIP 5%	10%

Filtered State Classification (ClassAct)

- ClassAct is a human posture / activity classifier based on decision trees.
- Similar to L-SIP, it transforms a raw signal into a representation of the state.
- Different to L-SIP, it is not possible to reconstruct the original signal.
- ClassAct estimates the state through decision-tree recognition of posture
- A voting filter is required and so the state is stored as a probability distribution over the set of postures

Evaluation of ClassAct

- Message Reduction
- 5182 classification packets were sent across a total of 9.6 hours of trials (343,140 packets of raw data)

• ClassAct is an instantiation of G-SIP that compresses a high frequency signal (accelerometer data) by first converting it to an application specific form.

Time-Discounted Histogram Encoding (BN)

- Bare Necessities (or BN) is used for summarising relative time spent in given states.
- Useful for determining how long is spent in a certain modality.
- The state is encoded as a distribution over bins.
- BN weights more recent measurements more highly than older measurements by applying a time discount factor γ.

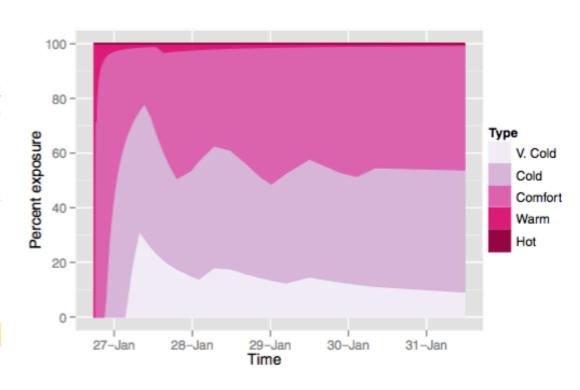


Fig. 4. Time-discounted temperature distribution over time for a monitored bathroom.

Evaluation of BN

Message Reduction

- Compared to L-SIP and ClassAct, BN has the most specific application requirement.
- Privacy issues can be subtle

TABLE IV

COMPARING THE PERFORMANCE OF BN ($t_{1/2} = 1$ Month) With L-SIP FOR ONE YEAR OF TEMPERATURE DATA [5]

	Transmissions	% of raw	RMSE in band %
Raw	102236	100%	n/a
L-SIP	2900 ± 700	2.8%	0.9 ± 0.2
BN	15 ± 6.5	0.02%	12 ± 4

Conclusion

- This paper has presented *edge mining*, a data-driven approach that transforms data at the point of sensing into a sparse form to reduce packet transmissions, energy use, and storage space.
- L-SIP applies to sensing applications where it is desirable to reconstruct the original signal within some error bound.
- ClassAct is a human posture recognition approach that just transmits or stores posture and the timing of postural changes but not the original accelerometer signal.
- BN discards even timing and is appropriate where only a summary of relative time spent in different states is needed.