Information Bang for the Energy Buck: Towards Energy- and Mobility-Aware Tracking

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What's the paper about?

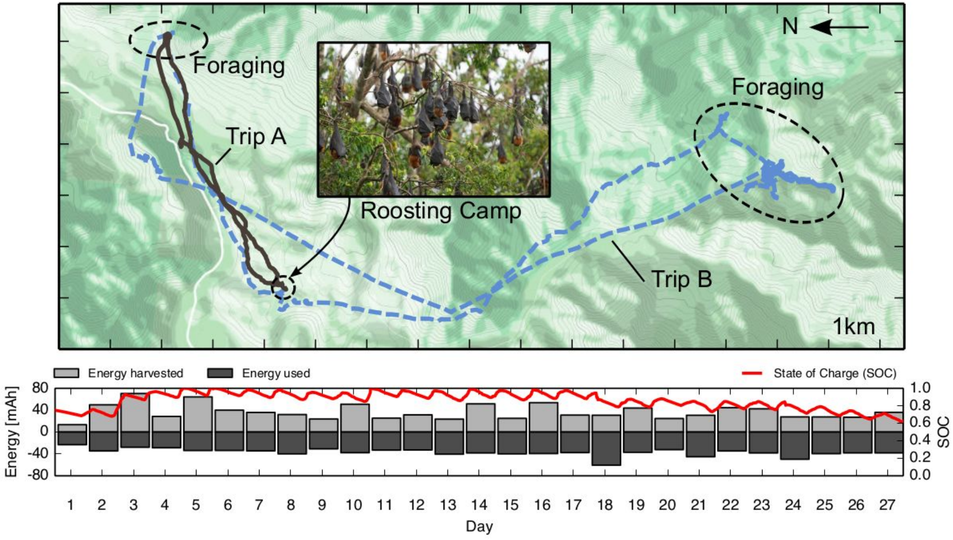
- Long term tracking of small, moving things
- Application - tracking flying foxes on foraging flights
- Estimating energy budget and motion duration
- Scheduling of high-power GPS sampling operations
  - Static
  - Adaptive
  - Information-based
- Collection of real trajectories, empirical comparison of methods

Motvation

- GPS sampling - high energy operation
- Trade-off between positioning accuracy and energy consumption
- “Hard” energy budgets for WSNs - cannot exceed
  - Use of harvested energy - near perpetual autonomous operation
- Vis-a-vis related work:
  - Usually - optimize energy for given accuracy constraint
  - Here - optimize accuracy for constantly evolving energy constraint

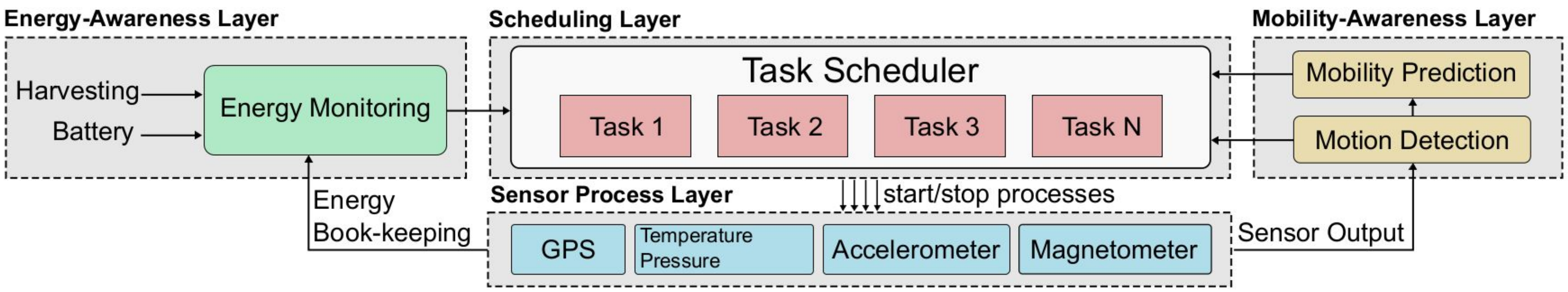
Motivation - tracking flying foxes (fruit bats)

- Spread disease, ravage fruit farms
- Solar cells recharge during day
- Forage at night, sleep at camp
- Size constrained (0.6-1 kg)
- Long observation periods
- Highly variable behavior



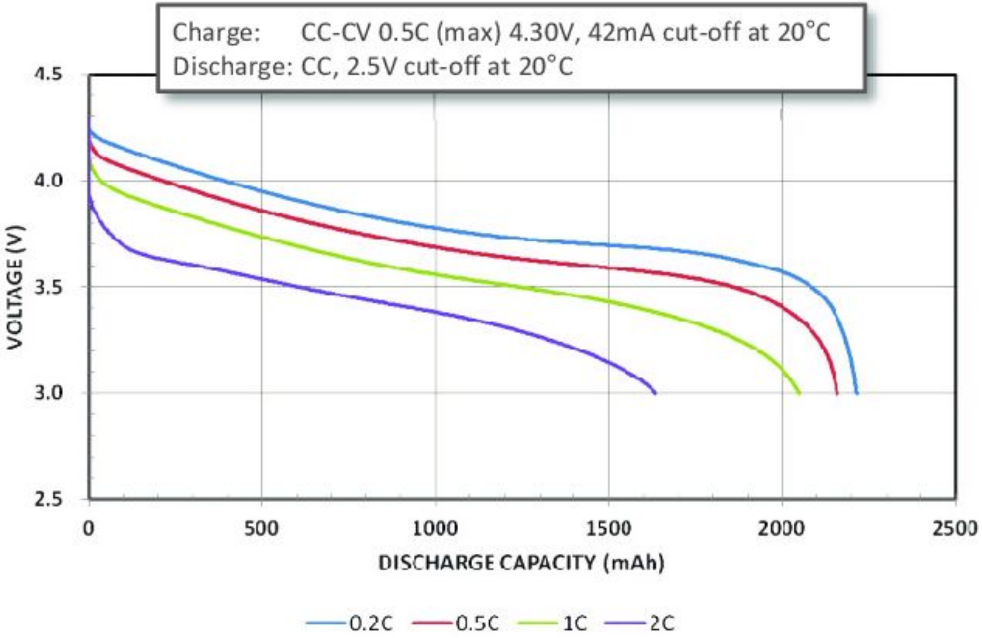
Approach framework

- Mobility awareness - motion detect, position error estimate
- Energy awareness - battery state through book-keeping estimates



Energy awareness

- Key metric - state of charge (SOC)
- Direct estimation from battery voltage difficult



Energy awareness

- Key metric - state of charge (SOC)
- Book-keeping approach
  - Solar panel voltage, current ↠ E harvested
  - Component operating states, consumption data ↠ E consumed
  - Sampled periodically, possible cross reference with voltage
  - Claim - accurate within 10%

$$SOC(t+\tau) = SOC(t) + E_{\text{harvested}}(t+\tau) - E_{\text{used}}(t+\tau) \quad (2)$$

Mobility awareness

- 3-axis accelerometer
  - Conditional task scheduling - interrupt when in motion
  - Used for motion detection
- 3-axis magnetometer
  - Used for heading detection in dead reckoning

Mobility awareness

- Activity classification
  - Continuous accelerometer sampling at 10Hz
  - Accumulate absolute deltas on z-axis
  - If value > threshold ↠ bat is flying
- Threshold
  - Population-wide
  - Determined from empirical GPS data
- Performance
  - In GPS data - 1m/s ↠ moving
  - 98.6% accuracy

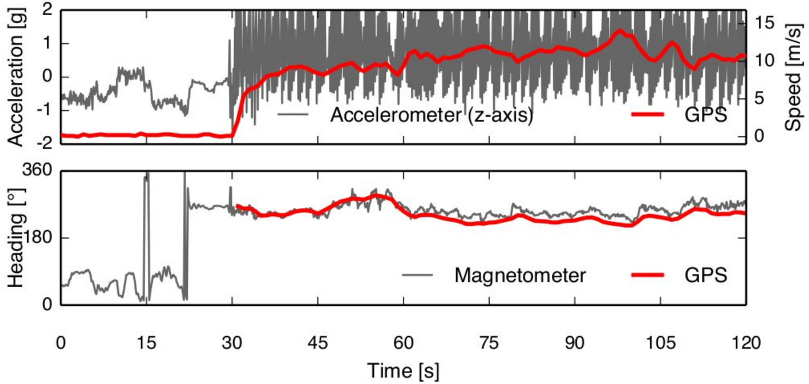


Figure 3: Timeline of z-axis accelerometer and GPS speed (top), and magnetometer heading and GPS speed (bottom) as the animal starts flying at t=30 s.

Mobility prediction

- More samples
  - More accurate trajectory data
  - More energy spent
- Sparse sampling while stationary
- Need to know how much longer the bat will be in flight

Mobility prediction

- Motion time, average speed, previous max distance - from previously observed or population data
- Total flight distance - individual- or population- based model
- Initially model dominates
- Late in the night - distance to base dominates

Algorithm 1 Mobility Prediction

```
Require: d_camp(t)                              ▷ Current distance to camp
Require: d_prev_max                             ▷ Previous max distance from camp
Require: Δt_motion                              ▷ Estimate for motion duration
Require: d_total(d)                             ▷ Estimate of total flight distance
Require: t_start, t_end                         ▷ Observation interval
  procedure PREDICT_REMAINING_DISTANCE(t)
    if d_camp(t) < d_prev_max then
      α ← (t − t_start) / (t_end − t_start)     ▷ Weight factor
      d_remaining(t) ← (1 − α) · Δt_motion · v_avg + α · d_camp(t)
    else
      d_remaining(t) = d_total(d_camp(t))
    end if
  end procedure
```

GPS sampling strategies

- Static
- Adaptive
- Information-based
- (for validation) Offline
- Most samples - "hotstart”

GPS sampling - static

- Motion based
- From prior data estimate
  - Energy budget
  - Motion interval
- Derive constant sampling interval

$$E_{\text{used}} = \Delta t_{\text{interval}} \cdot P_{\text{baseline}} + k \cdot T_{\text{hotstart}} \cdot P_{\text{tracking}}$$

$$k = \left\lfloor \frac{\Delta t_{\text{motion}}}{T_{\text{sampling}}} \right\rfloor$$

GPS sampling - adaptive

- Motion based
- Energy budget from measurements
- Remaining time interval - evolving estimate
    - Population- or Individual- based models for remaining distance modelling

$$E_{\text{used}} = \Delta t_{\text{interval}} \cdot P_{\text{baseline}} + k \cdot T_{\text{hotstart}} \cdot P_{\text{tracking}}$$

$$k(t) \leq \frac{E_{\text{budget}} - \Delta t_{\text{interval}}(t) \cdot P_{\text{baseline}}}{T_{\text{hotstart}} \cdot P_{\text{tracking}}}$$

$$T_{\text{sampling}}(t) = \frac{\Delta t_{\text{motion}}(t)}{k(t)} \qquad D(t) = \frac{k(t) \cdot T_{\text{hotstart}}}{\Delta t_{\text{motion}}(t)}$$

GPS sampling - information based

- Get velocity during GPS sample phase
- Magnetometer readings - cheap energy wise
- Estimate error based on change in heading over time
    - Not mentioned - time dependent error parameter?

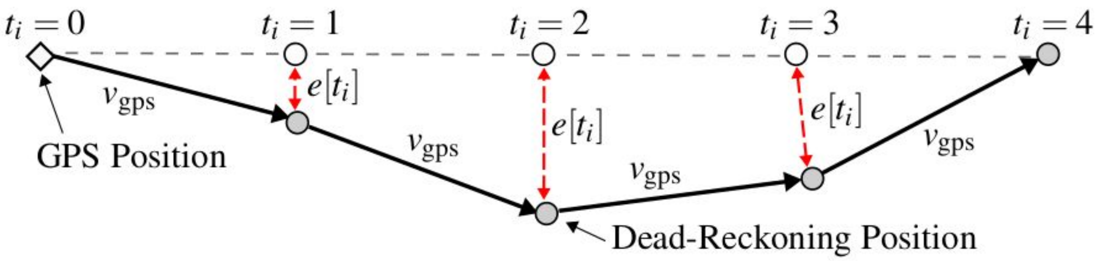


Figure 4: Dead-reckoning based on heading estimation using magnetometer data. The current position is extrapolated from the last known GPS position and speed v_{gps}.

GPS sampling - information based

- Duty cycle computed same as in adaptive sampling
- $R(t)$ – adaptive position error threshold
- $R(0)$, β – tuning parameters
- High $D(t)$ – aggressive sampling; low $D(t)$ – quickly enter conservative regime

$$E_{\text{used}} = \Delta t_{\text{interval}} \cdot P_{\text{baseline}} + k \cdot T_{\text{hotstart}} \cdot P_{\text{tracking}}$$

$$R(t) = R_0 \cdot \left(\frac{1}{D(t)} - 1\right)^{\beta}$$

$$k(t) \leq \frac{E_{\text{budget}} - \Delta t_{\text{interval}}(t) \cdot P_{\text{baseline}}}{T_{\text{hotstart}} \cdot P_{\text{tracking}}}$$

$$T_{\text{sampling}}(t) = \frac{\Delta t_{\text{motion}}(t)}{k(t)} \qquad D(t) = \frac{k(t) \cdot T_{\text{hotstart}}}{\Delta t_{\text{motion}}(t)}$$

Optimal offline benchmark

- Ground truth data - constant rate sampled trajectories
- Trajectory - sequence of points
- Given: energy budget
- Find: subsequence with minimum worst case error
- Graph shortest path problem - solved in polynomial time

Experimental setup

- 10 bats with collars
- 59 trajectories
- Empirical trajectories
  - Motion trigger at 2g
  - Collect GPS data at 1Hz
  - Terminate when $v < 5 m/s$
  - Enter power saving mode below energy threshold until battery recharged
  - Collect - position, acceleration, GPS heading as stand-in for magnetic
- Simulate methods on data set

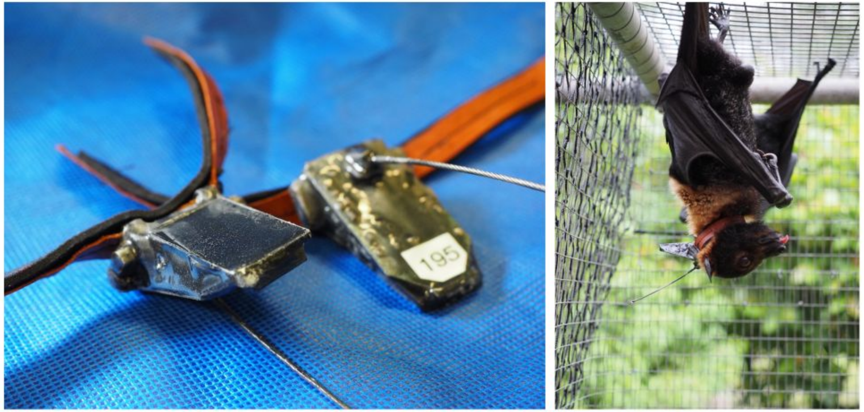
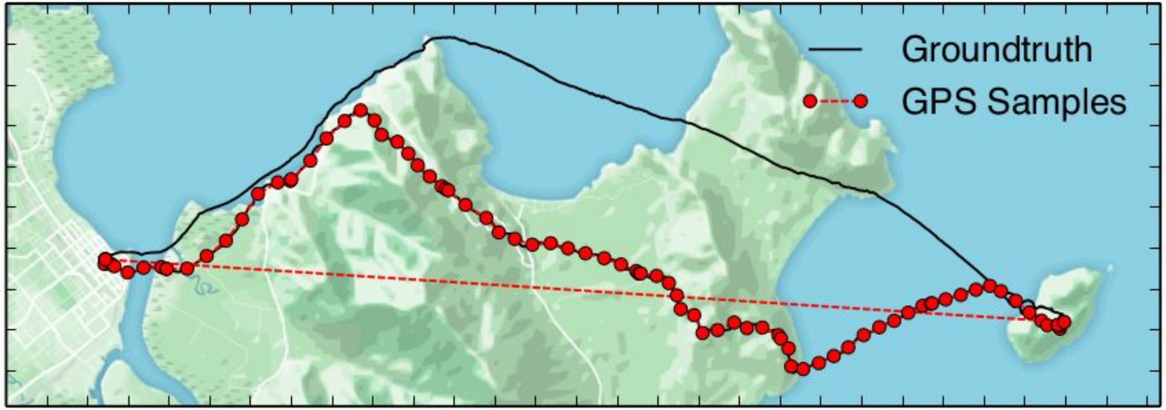


Figure 5: Camazotz collars (left) and a spectacled flying fox (Pteropus conspicillatus) with collar (right).

Method comparison - visual example

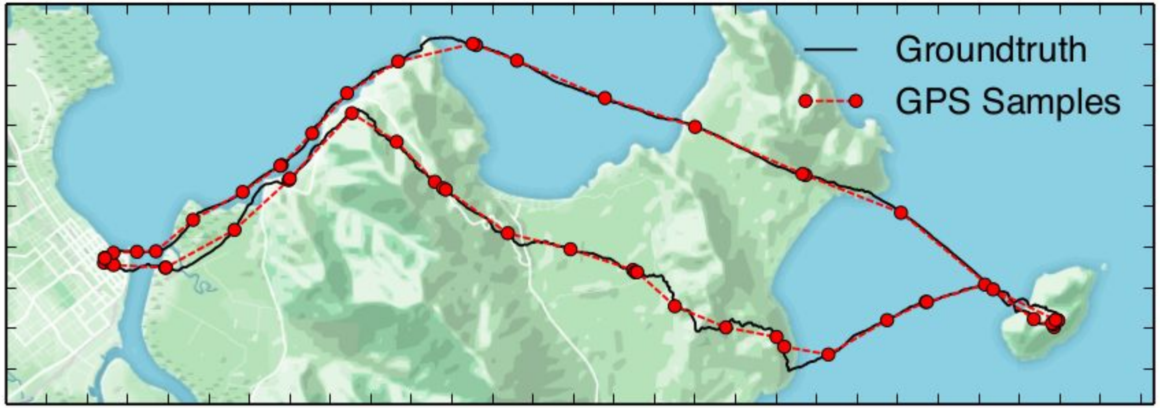
- Static - runs out of energy when trajectory longer than expected



(a) static motion-based tracking, population-based prediction of movement duration

Method comparison - visual example

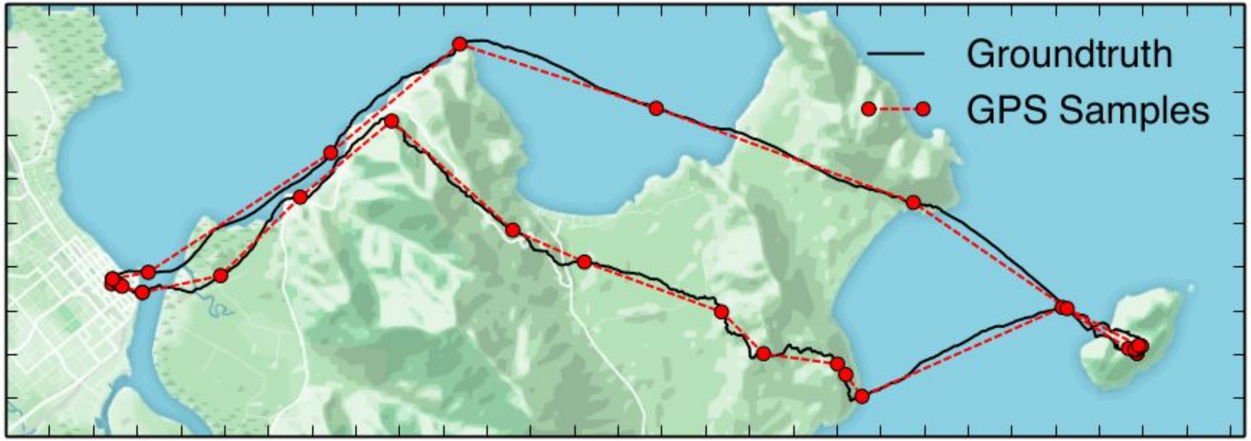
- Adaptive - better budgeting, not very good in highly twisting sections



(b) adaptive motion-based tracking, individual-based prediction of movement duration

Method comparison - visual example

- Information based - still fewer samples, better approximation near corners



(c) information-based tracking, individual-based prediction of movement duration

Energy and time estimates

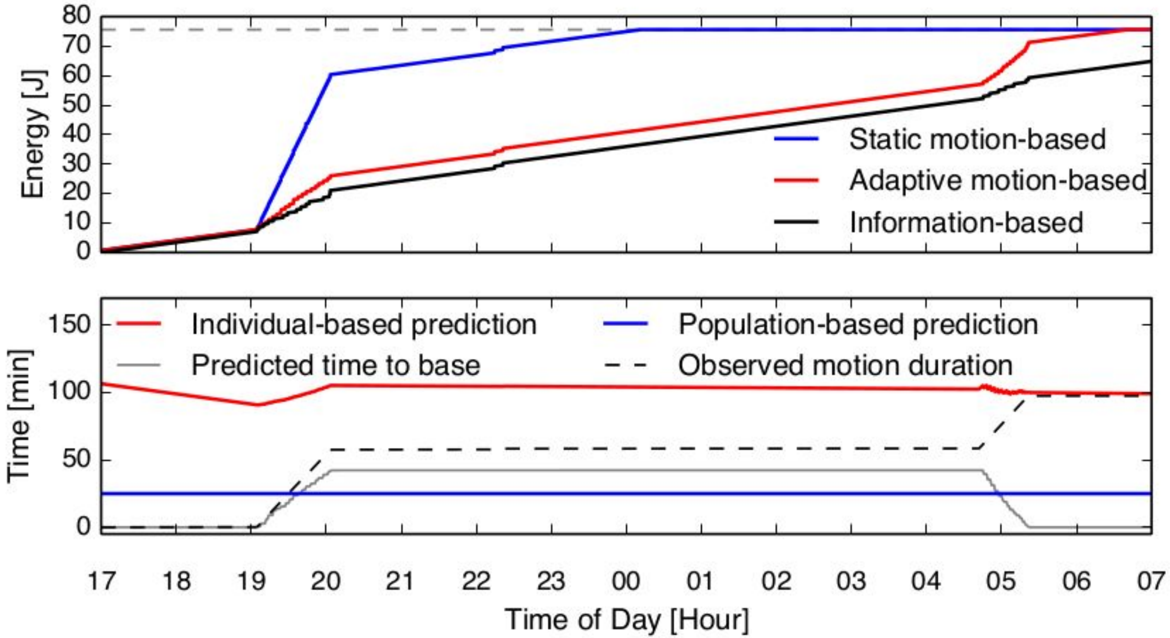
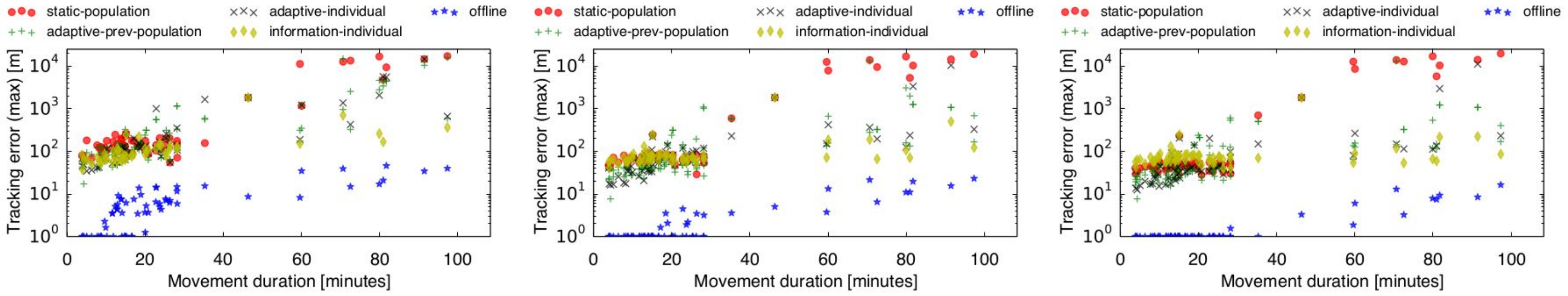


Figure 9: Energy consumption (top) and motion duration (bottom) for an example GPS trajectory of a flying fox.

Performance



(a) Budget: 1.5 mW (b) Budget: 2.25 mW (c) Budget: 3 mW

Figure 10: Distribution of the resulting maximum tracking error on the flying foxes dataset for different tracking strategies given an energy budget corresponding to an average power consumption of 1.5, 2.25 and 3 mW during the observation period.

Performance

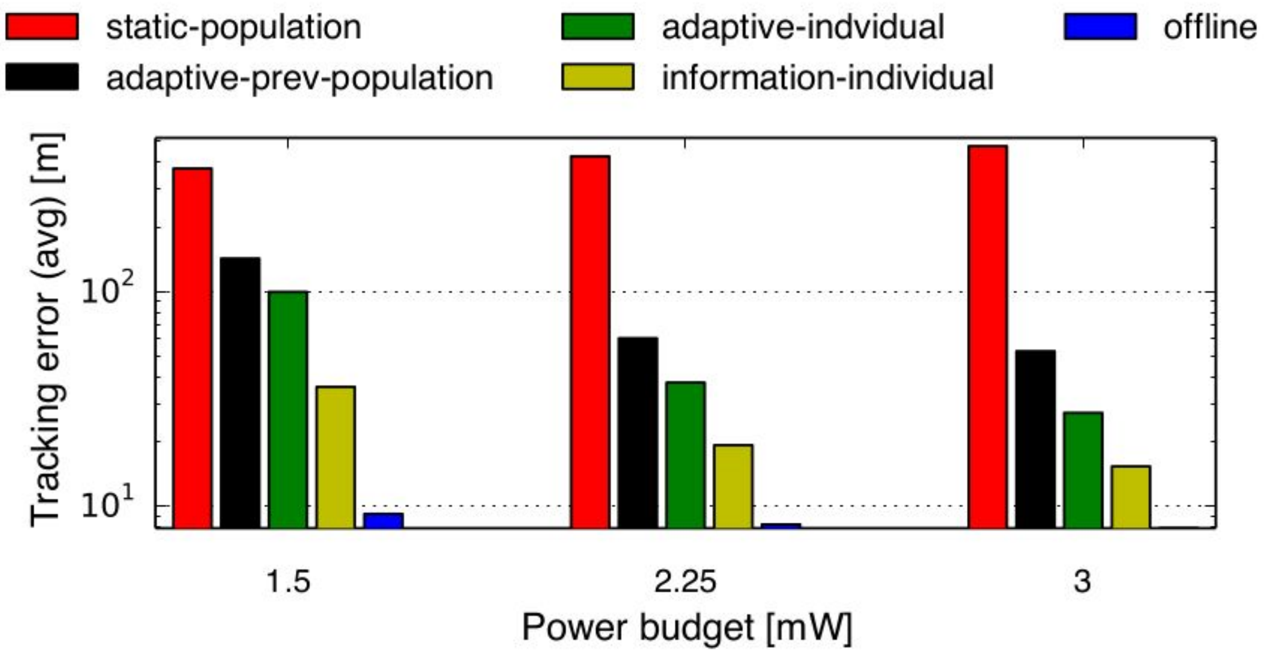


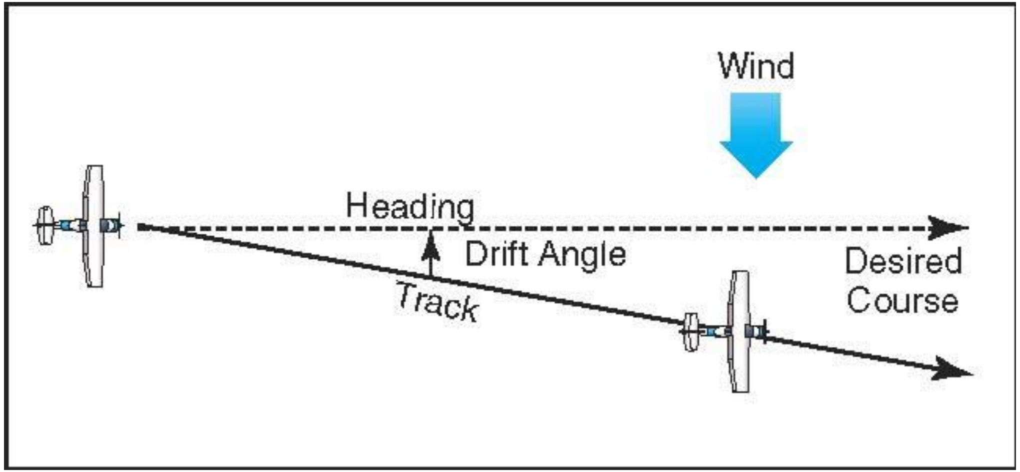
Figure 11: Average tracking errors for different strategies given a specific energy budget on the flying foxes dataset.

Performance - conclusions

- Population-adaptive roughly comparable to individual-adaptive
  - Previous day's population statistics vs individual's past statistics over multiple days
- Information based significantly outperforms other methods in average error
  - At 1.5mW:
    - 96% over static
    - 75% over population-adaptive
    - 64% over individual-adaptive
- Advantage of adaptive methods over static when flight durations are longer
- Information based methods do better at accuracy in winding paths and save much more power on easily-interpolated straight paths

Key oversight?

- GPS velocity vector != magnetometer heading
- No way to detect wind drift
- Need to introduce time-decay parameter - do advantages disappear?



Discussion

- Information-based approach - potentially improved by more sophisticated trajectory modelling and interpolation
- Use of environmental data for finer behavior modelling
- Uses in other fields
  - Humans behave like bats - move mostly between few key areas
  - Tracking of unpowered assets in logistics

Image sources

- Battery discharge curves: https://www.researchgate.net/profile/Yukai-Chen/publication/319269655/figure/fig1/AS:613911090962442@1523379218615/Discharge-curves-for-the-example-Panasonic-battery.png
- Wind drift https://miro.medium.com/max/1290/1*Y3rudqjdtfXRWnSDbAKDBQ.jpeg

Thank you for your attention!