Robust localization algorithms for an autonomous campus tour guide

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Outline

- The task and its technical challenges
- The localization problem
- Adaptive state estimation
- Experimental results
- Related work and conclusions

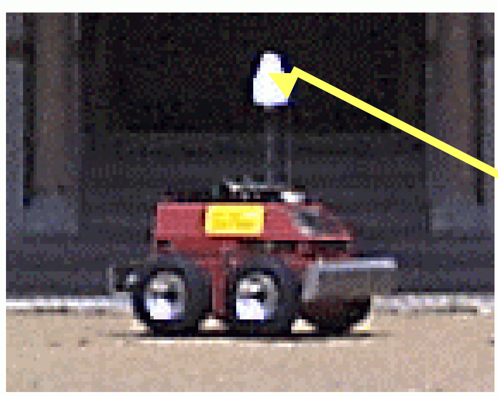
The task and its challenges

- Task: To give tours of the Rice University Campus.
- Challenges
  - Environment cannot be modified to assist robot.
  - Low budget project --- no expensive sensors!
  - Robot needs to interact with people.
  - Localization errors of more than 40 cm cannot be tolerated. Cost of failure high!

Virgil: The Rice Tour Guide

On-board odometry

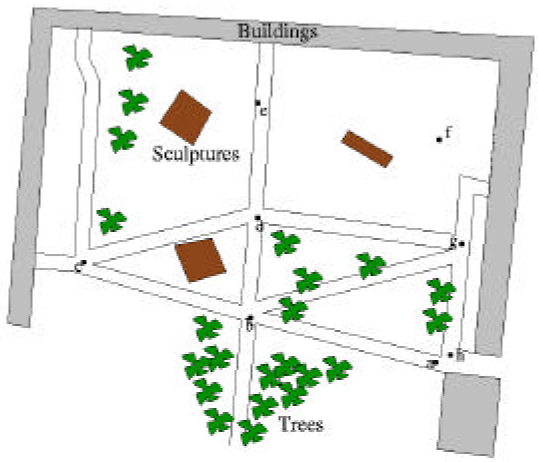
Sonars and bumpers for collision avoidance



RWI ATRV Jr equipped with cheap differential GPS ($2K)

Supported by a grant from Rice's Engineering School

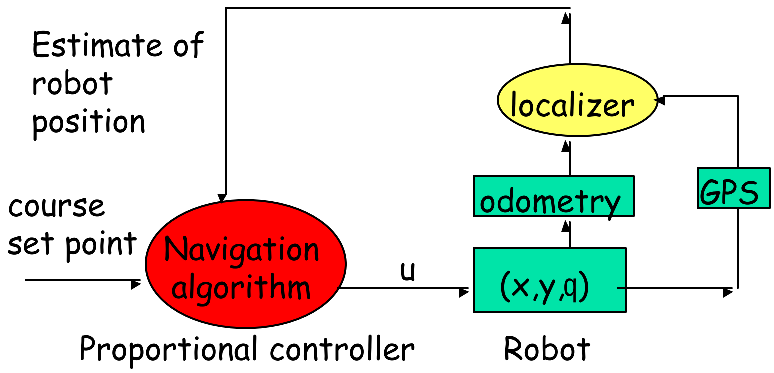
The Engineering Quad Tour



Engineering question

- How well can we localize the robot in an urban campus with lots of buildings and trees with cheap differential GPS (1s error of over 1 meter) and on-board odometry?

The localization problem



Localizer estimates robot position from odometry and GPS using an extended Kalman filter.

EKF basics: state evolution

- State X of robot evolves according to the following equation

$$X_{t+1} = f(X_t, u_t, w_t)$$

  - f is a non-linear function (f is estimated off line by a state identification process).
  - u_t is the commanded translation and rotation at time t.
  - $w_t = N(0,Q_t)$ is the "process noise".

EKF (contd.): Measurement

- GPS reading z measures the state X of the robot.

$$z_t = h(X_t) + v_t$$

  - v_t=N(0,R_t) is the "measurement noise".
  - h is a coordinate transformation.

The EKF calculation

- Recursive least squares estimation technique for computing X_t from a sequence of measurements $z_1,\ldots,z_t$.
- Two phase calculation
  - Prediction: from the estimate of state at time t-1, and the commanded action at time t-1, predict state at time t. (uses odometry)
  - Correction: Using measurement of state at time t, it corrects the previously derived state estimate. (uses GPS)

Extended Kalman filter

- Prediction

$$\hat{X}_{t+1} = f(X_t, u_t, 0)$$
$$\hat{P}_{t+1} = A_t P_t A_t^T + Q_t$$

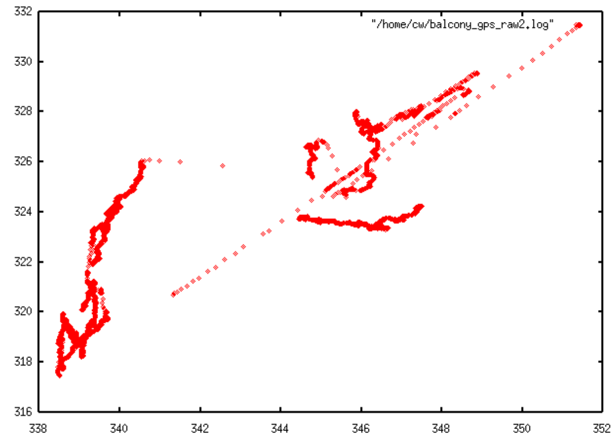
- Correction

$$X_{t+1} = \hat{X}_{t+1} + K(z_{t+1} - \hat{X}_{t+1})$$
$$P_{t+1} = (I - K)\hat{P}_{t+1}$$
$$K = \hat{P}_{t+1}(\hat{P}_{t+1} + R_t)^{-1}$$

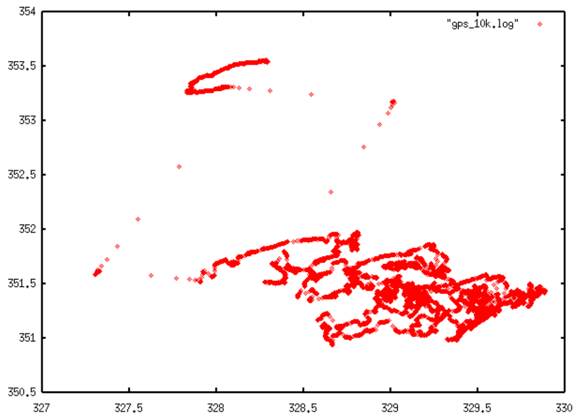
How well does EKF work?

- To accommodate large variation in GPS data quality, we pick a large value of measurement error variance R_k.
  - This causes slow convergence even when data quality is high!
  - Shifts in GPS data quality are not handled well; e.g., when robot emerges into a clear area with many visible satellites, it takes a while before localization accuracy reflects the quality of the GPS data.

GPS data (near buildings)



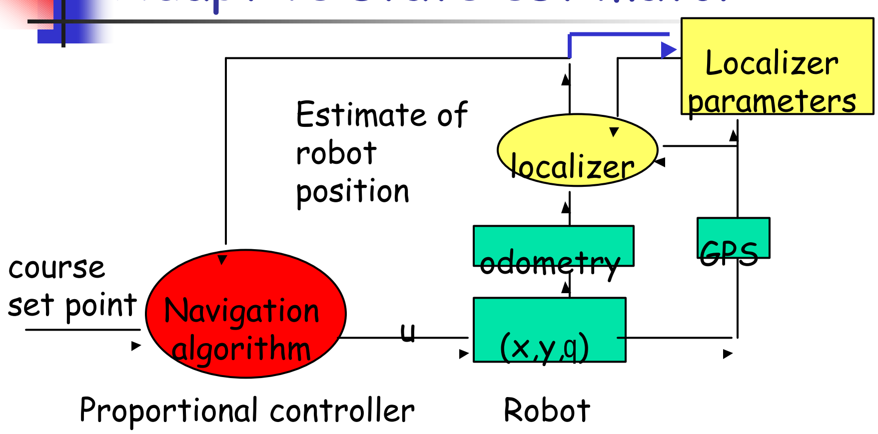
GPS data (in clear space)



Characteristics of GPS data

- Abrupt shifts in GPS data quality when satellites drop out of view (e.g., when robot is near concrete buildings or travels under trees).
- Gradual drifts in GPS data quality caused by atmospheric effects.

Adaptive state estimator



Adaptive state estimator

- For abrupt shifts in GPS data quality: Learn measurement error R indexed by number of visible satellites. Use "gain scheduling" and swap in appropriate R for current number of visible satellites at each time t.
- For gradual shifts in GPS data quality: use "exponential forgetting", i.e., use a window of N (=100) GPS observations and update R_t based on it.

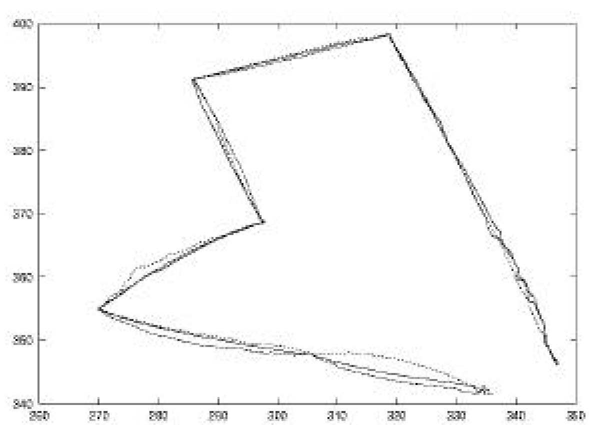
Experiment

- Hypothesis
  - an adaptive EKF based state estimator that handles time-dependent errors in GPS signals correctly will outperform a non-adaptive EKF based state estimator.
- Experimental set up
  - repeated runs of the Engineering Quad Tour with adaptive and non-adaptive state estimation.

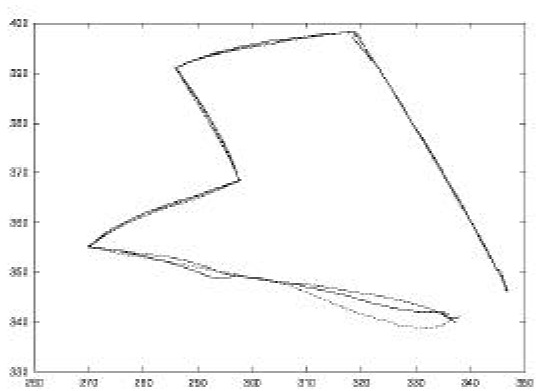
Evaluation metrics and results

- Ratio of length of actual path taken to the shortest path between via points on tour.
  - Non-adaptive EKF – 1.33
  - Adaptive EKF – 1.08
- Mean and standard deviation of the difference between true heading and heading as estimated by odometry sampled at 10Hz through the tour.
  - Non-adaptive EKF – 2.05 (1.64)
  - Adaptive EKF – 1.33 (1.54)

Results with non-adaptive EKF



Results with adaptive EKF



Related work

- Use of EKF for fusing odometry and GPS data in several papers including Goel et. al. IROS 99, Aono et. al. ICRA 98, Sukkarieh et. al. ICRA 98, Bouvet et. al. ICRA 2000.

Conclusion and future work

- Our contribution is in making the state estimation process adaptive by exploiting properties of the GPS signal. We use gain scheduling and exponential forgetting to handle GPS signal quality changes that occur at different time scales.
- We are working to extend the range of the tour to the entire campus, to build in safe mechanisms for crossing two busy streets on campus, and adding voice recognition to interact with tour groups.
- We are now starting to compare EKF based sensor fusion methods to particle filter methods.

A video of Virgil

Video made by William Diegaard of Rice University