Assessment of Energy Efficient Planning

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ARL RCTA

Robotics Collaborative Technology Alliance

- Fundamental and applied research to change robots from tools into teammates
    - Universities & Labs (e.g. FSU, CMU, UCF, Upenn, JPL)
    - Companies (GDLS, RR)

- ARL develops technology and assesses RCTA partners work

Skid Steering and Planning

- Skid steer vehicles turn by having wheels/tracks slip and/or skid
  - Robust and easy to maintain
  - Sharp turns increase motor torque (maybe beyond limit)
  - Result can be higher energy use
  - Idea: plan a path reducing sharp turns
  - Gain: potentially more energy efficient and fewer collisions

- FSU/CMU developed a planner intended to plan paths constrained by keeping turns within torque limits.
- These limits are terrain dependent, so learning is required to inform the constraints.

Energy Efficient Planner

- Start with theoretical model of robot dynamics (requires friction).
- Power model: torque as learned function of commanded turn radius.
- Models are combined to create constraint for turn radius.
- Path planning samples possible paths, with a heuristic preference for energy efficient ones, rejecting those that violate constraint.
- Details “Learning of Skid-Steered Kinematic and Dynamic Models for Motion Planning” Camilo Ordonez, Nikhil Gupta, Brandon Reese, Neal Seegmiller, Alonzo Kelly, Emmanuel Collins

Kinematic Model

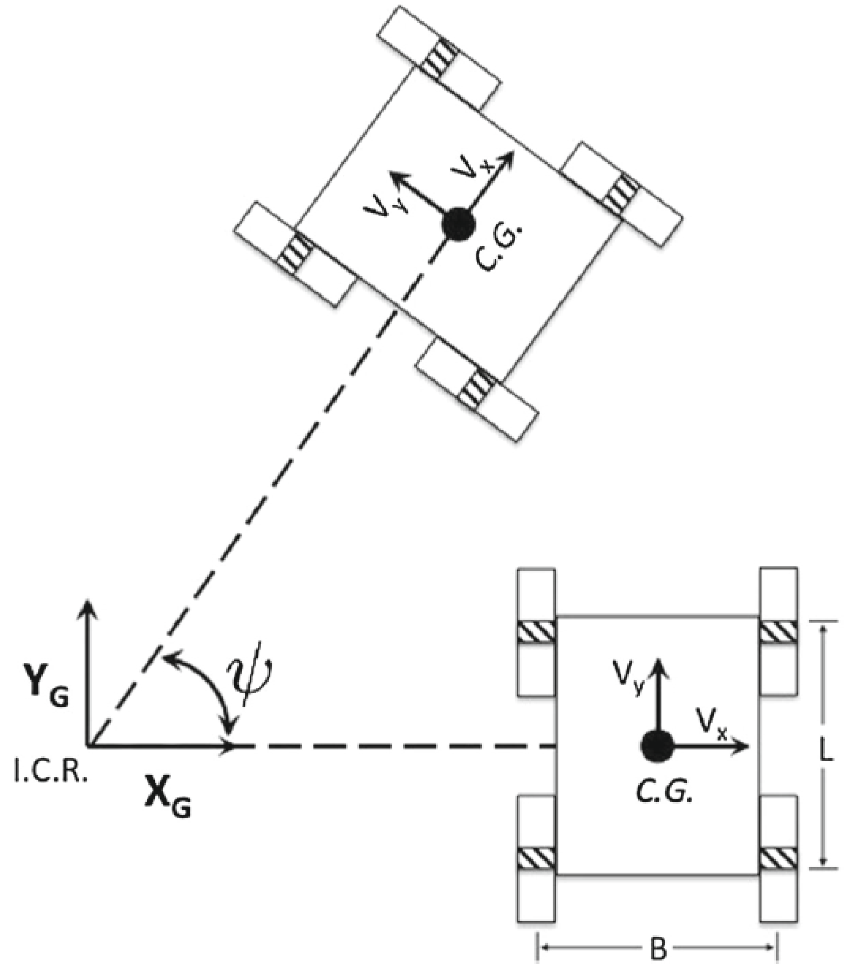


Fig. 1 A skid-steered vehicle performing a circular turn at constant velocity

$$\begin{bmatrix} v_y \\ \psi' \end{bmatrix} = \frac{r}{\alpha B} \begin{bmatrix} \frac{\alpha B}{2} & \frac{\alpha B}{2} \\ -1 & 1 \end{bmatrix} \begin{bmatrix} \omega_l \\ \omega_r \end{bmatrix}$$

α is terrain parameter

r is wheel radius

ω is angular wheel velocity

Basis for dynamic model

Assume motion in a plane

Goal of Experiment

- Primary:
  - Does energy efficient planning (EE) use less energy than minimum distance planning (MD)?
    - Compare difference in energy use of EE and MD paired by course
- Secondary:
  - Does energy efficient planning (EE) use less energy than energy efficient planning without learning (EE*)?
    - Compare difference in energy use of EE and EE* paired by course
  - Does energy efficient planning result in fewer collisions (if any occur)?
    - Comparison method TBD

Equipment

Robot

- Clearpath Robotics Husky
- Stereo for visual odometry
- Lidar for obstacle detection

Variables / Factors

Recording

- Energy expended
- # collisions

Course factors

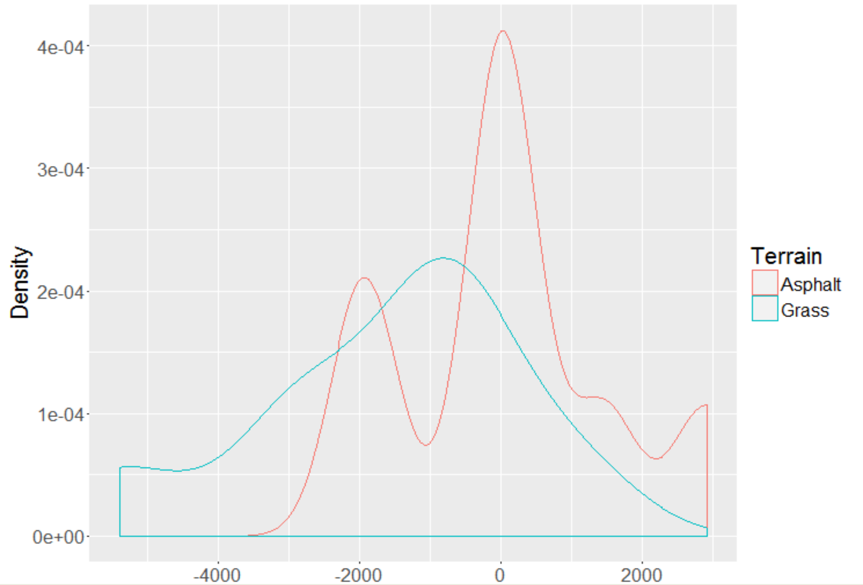
- Asphalt & Grass
- Configuration of Cardboard Obstacles
- Time for at most 40 runs (tropical storm)

Design

Surface	Obstacles	Planner
Grass	Config 1	Min. Distance
Grass	Config 1	Energy Eff.
Grass	Config 1	Energy Eff. No learn

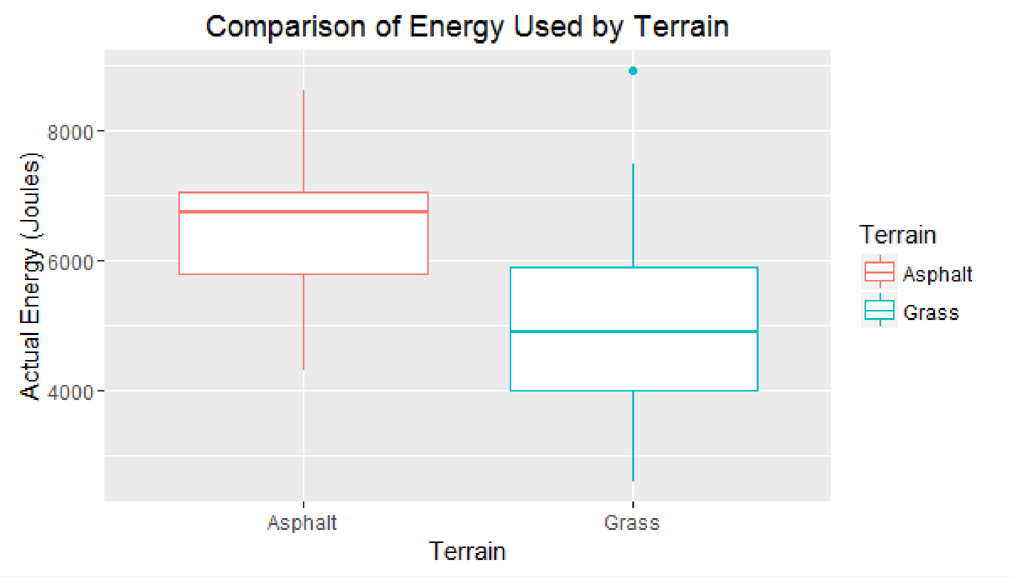
- 36 Runs
  - 18 Asphalt / 18 Grass
- Different terrain for variability
- 16 Configurations of obstacles
- Terrain & Configuration constitute blocks
- Planner order randomized within block
- 4 configurations included Energy Efficient planning without learning

Terrain Effects



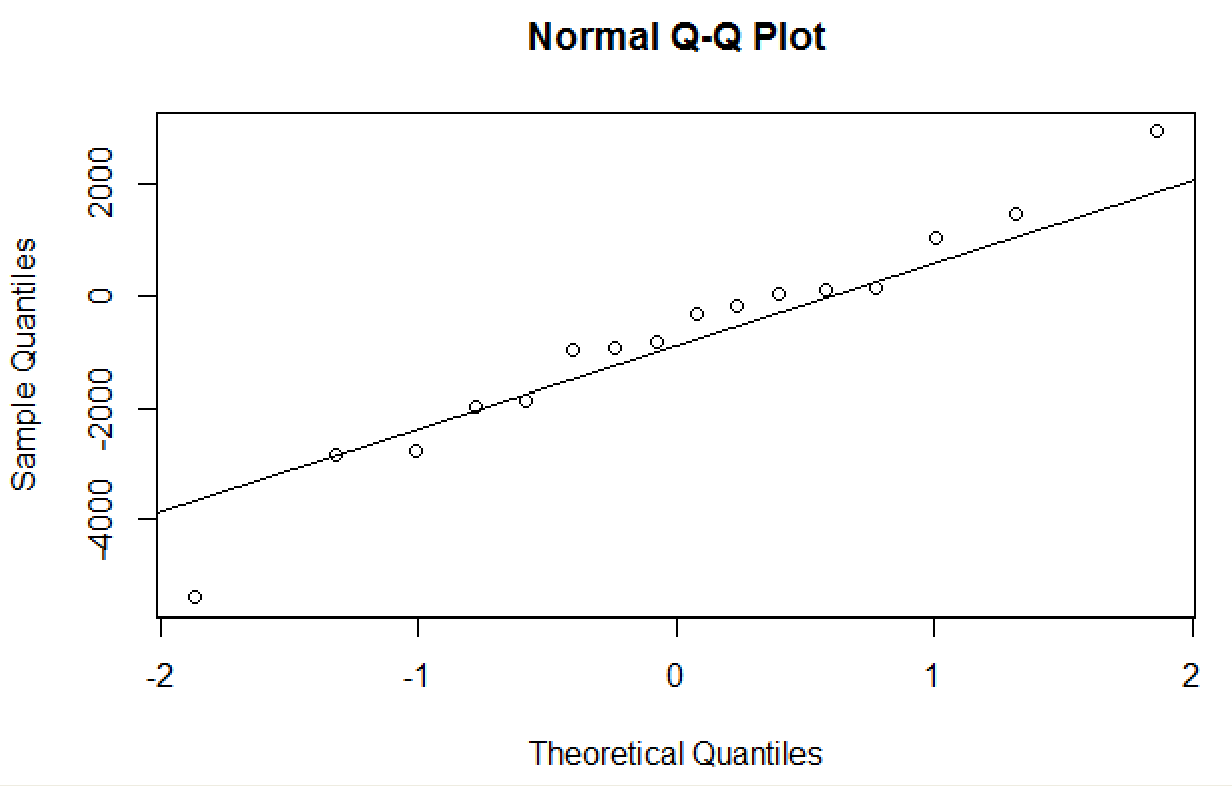
- Left: Difference in energy use by pairs Energy Efficient – Minimum Distance
- Possible difference by terrain

- Below: Energy used on each terrain
- More energy used on asphalt then grass



Normality of Differences

- Points represent observed difference in energy use (EE – Min Dist) within a pair



Aggregate Performance

- With extreme points
  - 16 pairs
  - 95% CI (-262, 1812) Joules of energy savings for EE
  - average of differences -775 Joules
  - Paired t-test: p-value 0.13

- Without extreme points
  - 14 pairs
  - 95% CI (-39, 1458) Joules of energy savings for EE
  - average of difference -710 Joules
  - Paired t-test: p-value 0.06

Collisions

# Collisions / # Runs		
Terrain/Planner	Min. Distance	Energy Efficient
Grass	5 / 8	0 / 8
Asphalt	0 / 8	0 / 8

Value of Learning to EE

- Does energy efficient planning work better with learning than without?
  - Virtually certain the answer would be yes at the outset
  - Really just a sanity check
  - 4 Pairs (2 sided t-test)
  - 95% CI (-137, 2644) Joules energy savings with learning
  - p-value 0.06

Conclusions

- Potential energy savings
  - Real life vs simulation
  - Seeing the whole map vs having it revealed
  - Extreme points are not measurement errors
  - Might see substantial savings with human checking
- Evidence for better collision avoidance on grass
  - Possibly to other slippery surfaces

Next

- We would like to test the algorithm further over a larger (sloped) course
- Test is of planning algorithm, not platform specific
- Try with a tracked platform or legged robot
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