

# **Robotic snow cat**

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## ABSTRACT

In recent years, break-through in GPS-navigation has led to a whole new range of robotic control applications. The Stanford University GPS laboratory has pioneered research in fields ranging from unmanned aerial vehicles, robotic open-pit mining trucks, and autonomous farm tractors. This same technology can also find use in grooming the slopes of a ski area!

With safety paramount, snow grooming is always performed after closing time of a ski resort, i.e. evenings and nights. Robotic snow cats have great promise for reducing current operating costs of snow grooming, partly due to cost of operators working extremely odd hours of the day. With a state-of-the-art navigation system, one may operate even in full whiteout conditions. Furthermore, a robotic vehicle could be more readily used in avalanche prone areas.

From the standpoint of a manufacturer, an autonomous snow cat has no need for an operator cabin (w/ chairs, controls, radios/CD-players etc.). Removing that cabin may well save weight as well as cost of production. Finally, cabin removal will open new degrees of freedom in snow cat design. A lower snow cat would be more stable, and it could more easily access areas under lifts.

As a first step towards the ultimate goal, a GPS-based autopilot for a Bombardier MP Plus snow cat has been implemented and tested. This paper gives a general system overview and presents results from field tests at Alpine Meadows Ski Resort. All tests were performed without any attitude system, but the results still show total system errors in the 10-cm range.

#### 1.0 Introduction

GPS based robotic systems are currently finding their way into the market place. GPS has enabled tractors to plow perfectly straight rows in farm fields [1], and huge trucks to navigate open pit mines [2]. The purpose of this paper is to explore similar technologies for robotic grooming of ski slopes.

There's more to using a snow cat than simply driving it around the ski slopes. Unlike most comparable heavy machinery, snow cats use both front and rear mounted implements. Whereas a front blade levels major snow unevenness, like moguls, a rear tiller removes snow lumps and residual surface unevenness. Both implements are 4-6 degree of freedom systems, and they're controlled through separate joysticks. Finally, snow cats are steered around either using steering wheels, or 2 "tank like" trackspeed control sticks.

Due to the plethora of controls involved in handling a snow cat, fully mastering such a vehicle is a skill that usually takes several seasons to acquire. Not only must a snow cat operator guide the vehicle along paths with minimum mutual overlap, but the operator must also make constant changes to the attitude of the front blade and rear tiller in order to ensure best possible grooming performance. Furthermore, a groomer must judge the oncoming snow surface in order to cut down all bumps and fill in all ruts, all while constrained by following natural terrain features. Finally, operators must adapt to a wide spectrum of snow conditions. Still, an expert groomer needs only one single pass through a mogul field to level it perfectly.

Snow grooming is always done after closing time of a ski resort, when no one is on the hills. Although public safety is maintained such scheduling means extremely odd working hours for snow groomers. Night work during weekends is rather expensive for ski resorts. Furthermore, some ski hills run only one shift of grooming. This means they require more \$200k snow cats to do the same job that other ski resorts do by grooming all night. In the quest to remain open to the public, snow cats are often run during whiteout conditions. Robotic snow cats with state-of-theart navigation systems should greatly improve grooming performance during low visibility conditions as well as reducing regular operating costs. Such robotic vehicles would have no use for an operator cabin. Removing that cabin should open new doors in snow cat design, e.g. enabling lower vehicles for easy access under lifts.

Although making a snow cat fully autonomous is the long-term goal of this project, systems for operator assistance can be achieved more readily. Removing some of the workload from an operator should improve grooming and cut down on initial training time. Thus, a GPS-based snow cat autopilot was implemented to test one possible technology.

#### 2.0 Experimental set up

In this work we had the great fortune of borrowing a Bombardier MP Plus snow cat from Alpine Meadows ski resort. We mounted a dual-frequency GPS antenna on the roof of the operator cabin and a UHF data link antenna to its right side-view mirror. A Trimble 7400 RTK-GPS receiver, a Pacific Crest Blue Brick UHF data radio, and a 300W power inverter were fastened to the inside of the operator cabin. Then, an Industrial Computer Source PC with a DBI "sunlight readable" LCD display and a 12V battery were fit snuggly on the passenger-side floor. Finally, a Phytek 515C microcontroller was attached to the top of the PC. See picture below for passenger-side equipment.



Figure 1 Technical equipment

As GPS reference, another 7400/Blue Brick pair was put on top of the start tower of the Subway lift at Alpine Meadows. See picture below.



Figure 2 GPS reference station

The full system overview is shown in the figure below.



Figure 3 Navigation and control system overview

The industrial PC ran the Lynx real-time operating system and communicated with both the 7400 and the microcontroller through serial interfaces. A separate process on the PC controlled each serial interface, and pipes were used to pass information to and from a third process running the real-time controller. The figure below shows data flow through the PC.



Figure 4 Real-time computer overview

Bombardier MP Plus snow cats are steered around using 2 track-speed control sticks, called FNRs. These FNRs contain potentiometers, and the on-board computer sets track speeds proportional to the given voltages across those pots. Using a microcontroller with digital-to-analog converters, we by-passed the FNRs altogether and steered the snow cat from our PC. The picture on the next column shows the operator seat of a Bombardier MP Plus.



Figure 5 Operator seat with FNRs

After testing all subsystems, the entire test area at Alpine Meadows was accurately surveyed. Using that data, paths for the snow cat to follow could readily be made.

During all tests two people manned the snow cat; an experimenter and a representative from Alpine Meadows. Keeping up a long tradition in field testing, this safety officer could independently stop the snow cat if something went wrong. Thus, keeping tests safe while enabling the experimenter to fully concentrate on the task at hand.

#### 3.0 Vehicle modeling

Previous work controlling tracked vehicles has shown that such vehicles can be modeled as unicycles [3]. The figure below shows a simple model for a snow cat.



Figure 6 Snow cat model

Here the snow cat body is modeled as a point mass for along-track motion, and as a slab of inertia for turning motion. Forces,  $F_1/F_2$ , between snow and the tracks propel the snow cat forward as well as turn it around. Friction forces, R and  $G \cdot \dot{q}$ , resist linear and turning motion respectively.

Along-track equation of motion

$$M \cdot \ddot{x} = F_2 - F_1 - R \qquad \text{Eq. 1}$$

Rotational equation of motion

$$I \cdot \ddot{\boldsymbol{q}} + G \cdot \dot{\boldsymbol{q}} = (F_1 + F_2) \cdot d$$
 Eq. 2

Since experiments mainly include line tracking, we only consider the rotational equation of motion for our control system. We linearize that equation, and put it on state space form.

In the above linearized equations  $y_e$  is perpendicular deviation from a curve,  $q_e$  is heading deviation,  $\dot{q}_e$ heading rate deviation and u is control input. Note that the 7400 GPS receiver only measures position and heading ( $z_1$ ,  $z_2$ ). However, heading rate becomes observable through our system model. Furthermore, all deviations are calculated when measurements are compared to a pre-programmed path. The parameters of the model include velocity, V, frictional coefficient of rotation, G, moment of inertia, I, and control input coefficient, N.

#### 4.0 Model parameter identification

Coarse estimates of snow cat model parameters can be found by looking at its weight, engine size, gearing ratios and geometric dimensions. However, some of these numbers were hard to come by, even reading through the snow cat specifications. Consequently, we tried measurement based system identification techniques instead.

In essence, one wants to input into a system a known signal with plenty of spectral content in the frequency range in question. By simultaneously observing system outputs, one can estimate effective transfer functions of a given system through FFTs. For the vehicle at hand, we decided to input chirp signals to the snow cat turning control and log heading data. Chirps are signals with constant amplitude, but linearly increasing frequency. Thus, chirps come out flat in frequency domain. The figure below shows a chirp input and a heading output for one experimental run.



**Figure 7 Input-output relations** 

A total of 11 runs were performed at 1 m/s speed; six of which had the snow cat tiller engaged, and five with the tiller disengaged. The reason for alternating the tiller was to find its effect on system dynamics. For the given speed and the given snow conditions, no substantial differences between the two cases were found. Thus, all 11 runs were used to best determine a single set of snow cat model parameters.



Figure 8 Bode plot for heading response

The figure above shows the Bode plot of the snow cat heading response. Whereas the yellow dotted lines are estimated transfer functions for the 11 different runs, the red line shows the median value of those experiments. The green line signifies the best fit of model parameters, G/I and N, to the experimental data (red line). Although model and measurements fit well in our region of interest, around 0.1 Hz, there's a significant difference between the two at higher frequencies. We believed that discrepancy stemmed from signal aliasing. Thus, we ran the same 11 chirp signals from our tests through our model. The blue line in the figure above shows the median value of those simulated responses. Since the blue line (model) and the red line (real system) match up well, we believe our system model is valid even at those higher frequencies.

#### 5.0 Path implementation

Although groomers frequently will back up their snow cats in order to turn around, these field tests lacked an attitude system so paths were made by connecting straight lines and circular arcs. In this way, a snow cat could always be run in the forward direction through its path.

For straight path segments we stored start position, its length, its reference heading, its reference speed, and unit vectors along and perpendicular to the line.



**Figure 9 Straight path segment** 

The figure above shows a snow cat along a straight leg. Whereas heading deviation,  $\theta_e$ , could be found by differencing measured and reference headings, position deviation,  $y_e$ , could easily be found from the equation below.

$$y_e = \vec{r} \cdot \hat{1}_y$$
 Eq. 5

A new segment was started if equation 6 held true:

$$\vec{r} \cdot \hat{l}_x > l$$
 Eq. 6

For curved segments we stored center position, its radius, its reference speed, its turn direction, and a unit vector tangent to its exit direction.



Figure 10 Curved path segment

The figure above shows a snow cat along a curved leg. Reference heading, tangent to an arc, was now calculated for each measurement point. However, position deviation could easily be found by differencing snow cat distance from the arc center and the arc radius (below).

$$y_e = \left| \vec{r} \right| - r_{ref}$$
 Eq. 7

Finally, segments were switched if the following equation held true:

$$\vec{r} \cdot \hat{1}_e > 0$$
 Eq. 8

A snow cat compensator would be provided with data independent of segment type by formatting paths in the manner above. Thus, hand-over between segments was virtually seamless.

#### 6.0 Controller structure

Even though a classical PID controller might have worked well, we decided to go with a more modern Linear Quadratic Gaussian (LQG) compensator for the problem at hand [4]. LQG compensators use Linear Quadratic Estimators (LQE ~ Kalman filter) to improve state estimates, and Linear Quadratic Regulators (LQR) to form control outputs based on the given states. See figure 11 for a discrete mechanization of LQG (DLQG).



Figure 11 DLQG mechanization

The following 3 equations describe a current Discrete Linear Quadratic Estimator (DLQE), a Discrete Linear Quadratic Regulator (DLQR) and DLQG state propagation.

$$\hat{x}_{k} = \begin{bmatrix} I - L_{d} \cdot C_{d} \end{bmatrix} \cdot \overline{x}_{k} + L_{d} \cdot z_{k}$$

$$u_{k} = K_{d} \cdot \hat{x}_{k}$$
Eq. 9
$$\overline{x}_{k+1} = A_{d} \cdot \hat{x}_{k} + B_{d} \cdot u_{k}$$

In the above equations z is measurements,  $\overline{x}$  is á priori state estimates,  $\hat{x}$  is á posteriori state estimates and u is control input. Whereas  $A_d$ ,  $B_d$  and  $C_d$  are model matrices from equations 3 and 4,  $L_d$  and  $K_d$  represent DLQE and DLQR coefficients respectively.

#### 7.0 Closed-loop path-following results

After simulating and testing several sets of compensator coefficients, we finally settled down on a fairly moderate set. The following two figures show 6 full runs of the snow cat autopilot at Alpine Meadows on March 22 2000.



Figure 12 Overview of autopilot experimental runs



Figure 13 Center leg of autopilot experimental runs.

In the previous plots, red dash dotted lines show desired snow cat paths. Whereas green lines show results from 3 runs with tiller engaged, blue lines signify runs with that implement disengaged. Not only did we want to learn how disengaging the tiller affected system dynamics, but we also needed visual queues for video taping the tests. Although GPS was the only means of navigation for these experiments, looking at track marks in the snow gave a qualitative answer on how well the system performed.



Figure 14 System states and control output

The plot above shows all three system states for one run and the corresponding control output. Blue lines are measured data while red ones are estimates.

Position	2.1	-3.0	-0.4	7.9	5.6	9.5
mean (cm)						
Position	31.6	32.9	27.2	34.3	36.7	33.3
std. (cm)						
Heading	-0.1	0.3	0.1	-0.2	0.1	0.0
mean (deg.)						
Heading	6.0	7.1	6.2	6.2	7.9	5.5
std. (deg.)						

#### **Table 1 Measurement statistics**

The table above shows mean bias and standard deviation in position and heading measurements for all 6 field tests on 3/22/00.

#### 8.0 Conclusion

Through these tests, we implemented the first known autopilot for a snow cat; a step towards an ultimate goal of fully autonomous snow grooming. Inspecting the results closely, one may find deviations from the desired path of up to 1 meter during turns, and transients of 0.5 meters when acquiring straight segments. Even though these errors clearly would exceed standards for an operational system, comfort can be taken in the fact that virtually the same deviations repeat in all runs (Fig. 13). Such consistency leads us to believe that a more "aggressive" compensator has the prospects of decreasing errors. Augmenting the compensator structure with integral control states and feed-forward elements may well further improve performance. However, results already show that sub-decimeter deviations are prevalent once initial transients die down (Fig. 13).

Engaging the snow cat tiller had no noticeable effect on system dynamics in any of our tests. We believe that the actuator authority presented by the snow cat's 275-HP engine played a large role here. Although we ran experiments on several occasions, other snow conditions as well as different hill pitch may affect our current findings.

GPS was our only means of navigation in these tests. Although the 7400 receiver provided acceptable navigation accuracy, availability of GPS proved rather poor. Mountains and trees at Alpine Meadows frequently blocked SVs so GPS was unavailable at certain times of day or at certain spots on the test hill. Still, the dual frequency nature of the 7400 was invaluable when it came to re-acquiring RTK-grade positioning fast. Finally, work is currently underway looking into options for augmenting GPS and more robustly navigating such environments.

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### References

- Elkaim, G., O'Connor M., Bell T., B.W. Parkinson System Identification and Robust Control of a Farm Vehicle Using Carrier-Phase Differential GPS ION-GPS 97, Kansas City, MO. September 1997.
- J.M. Stone, J.D. Powell Carrier phase integer ambiguity resolution using dual frequency pseudolites ION-GPS-98, Nashville, TN, September 17, 1998
- 3. Ping Lu and Kou-Chi Lin Nonlinear control of an autonomous tracked vehicle Trans Institute MC, Vol 16, No 4, 1994
- Franklin, Powell and Workman
   Digital Control of Dynamic Systems
   Fig 6.10 p 265, Addison & Wesley, 2.nd edition, 1992