Multi Sensor fusion and 2D State Estimation of Lunar Rover

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Introduction

In most mobile robot applications two basic position-estimation methods are employed together: *absolute* and *relative positioning* [1].

◆Absolute positioning utilizes navigation beacons, active or passive landmarks, map matching, or satellite-based navigation signals. These systems are usually expensive and complex in real application.

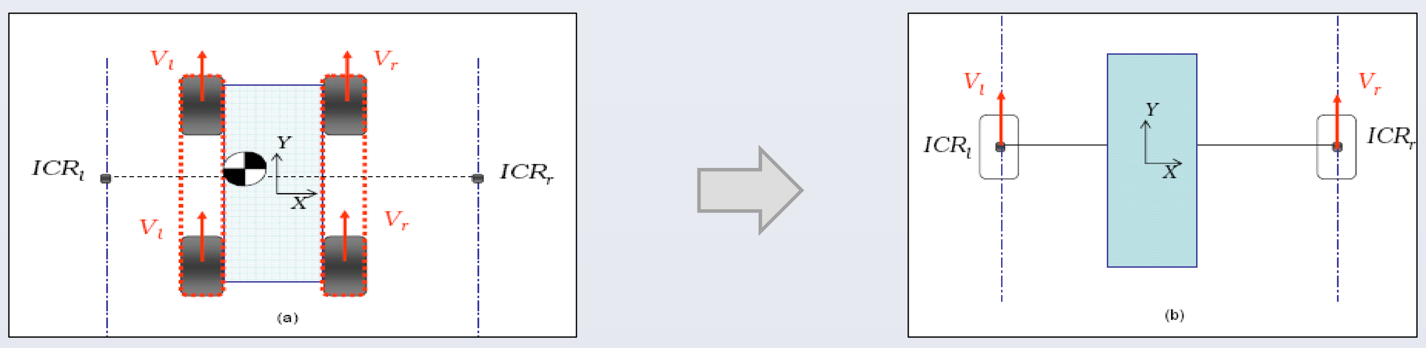
◆Relative positioning is usually based on odometry and inertial measurement units. While it is simple and in expensive. It suffers from unbounded accumulation errors.

Limitation of GPS signal on the moon and complexity of implementing map matching urges a reliable and powerful way to estimate the lunar rover's state using wheel odometry and inertial measurement units.

Model

Model simplification:

The experimental platform is a 4-wheel skid steer rover. However, the sliding interaction is often too complex to model accurately in application. For simplicity of development and testing, a differential drive approximation is utilized.



(a) (b)

Fig1. Kinematic equivalence between the tread ICRs of a skid-steer vehicle (a) and wheel contact points of an ideal differential drive vehicle(b).[2]

Dead Reckoning Using Wheel Odometry

Wheel odometry is based on assumption that wheel revolutions can be translated into linear displacement and rotation relative to the floor. Given encoder readings, gear ratio, wheel diameter, it is possible to calculate the 2D position of the rover.

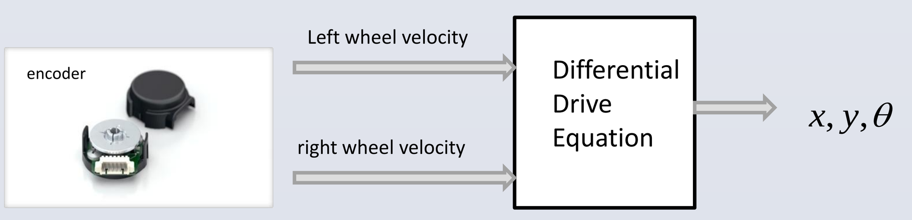


Fig2. 2D state estimation of encoder data

Tab 1. Parameters of encoder and wheel

Gear ratio	2048
Ticks per revolution	360
Wheel diameter	0.32 m
Wheel track	1.55 m

Inertial Measurement Units (IMU) Based Localization

The Crossbow IMU400CC is a high performance solid-state six degree-of-freedom (6DOF) Inertial Package . It provides raw measurement of angular rate and linear acceleration of three axes. Integration of these raw data provides a rough observation of the rover's state.

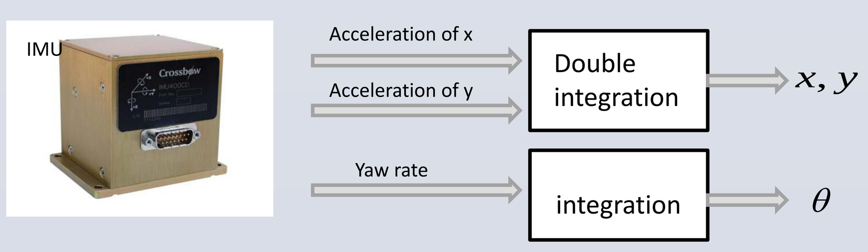


Fig3. 2D state estimation of IMU data

Tab 2. parameters of IMU

Range of gyroscope	
Range of acceleration	$\pm 100^0$ / sec
Bias of gyroscope	$\pm 4g$ / sec
Bias of acceleration	$\leq \pm 1^0$ / sec
	$\leq \pm 12mg$ / sec

Kalman Filter-----Combining Data from IMU and Wheel Odometry

The encoder readings are influenced by non-systematic errors like slip and the IMU data suffer from drift. In planetary applications, where other sensors are limited, a effective means of combining encoder and IMU data together is to use Kalman Filter. Taking the highly updated IMU data for the prediction step and relatively lowly updated encoder data for the measurement step will create more precise results than using single sensor.

Kalman Filter :

- ◆ State vector: $x = [x, y, v_x, v_y, \theta]_I$
- ◆ Input vector: $u = [acc_x, acc_y, \omega]_B$
- ◆ Measurement vector: $z = [v_x, v_y]_B$

I: fixed frame B: body frame

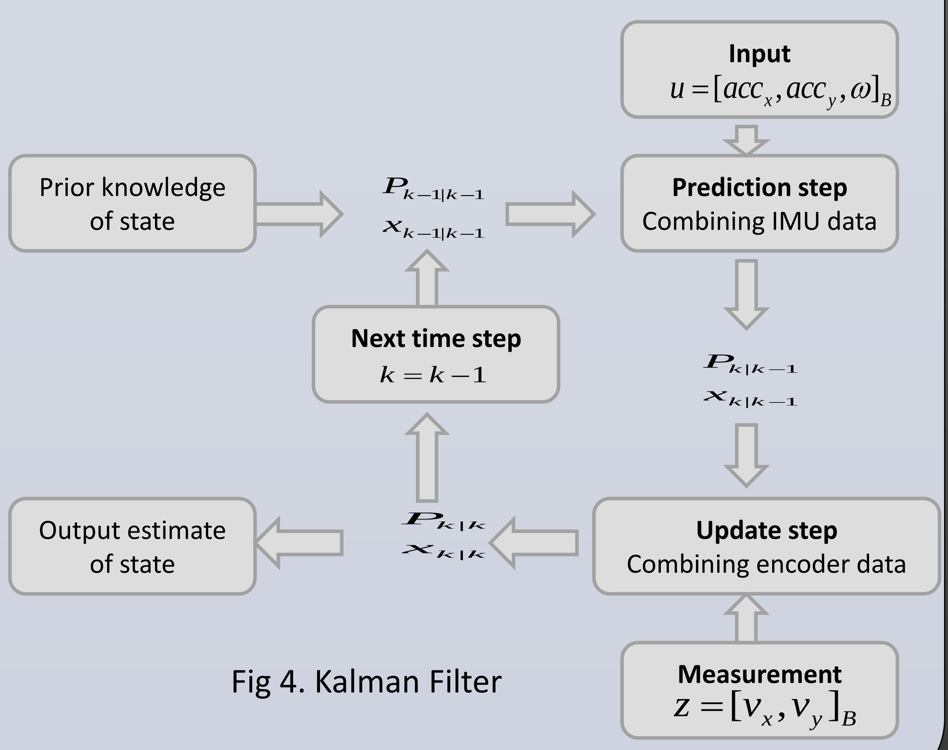


Fig 4. Kalman Filter

Fiber Optic Gyro

IMU is influenced by large drift rates, which cause unbounded drift error. Fiber optic gyro, which ensures exceptionally low noise and vibration robustness, provides more accurate heading estimation.

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Results

Field tests Environment

A lunar rover named Prototype 3 was used for test at CMU.

Test series include:

◆ **performance of IMU and encoder**

1. forward → stop → forward
2. pivoting 180 degree

◆**performance of gyro and encoder**

1. walking in a square shape
2. walking a straight line using PID control algorithm

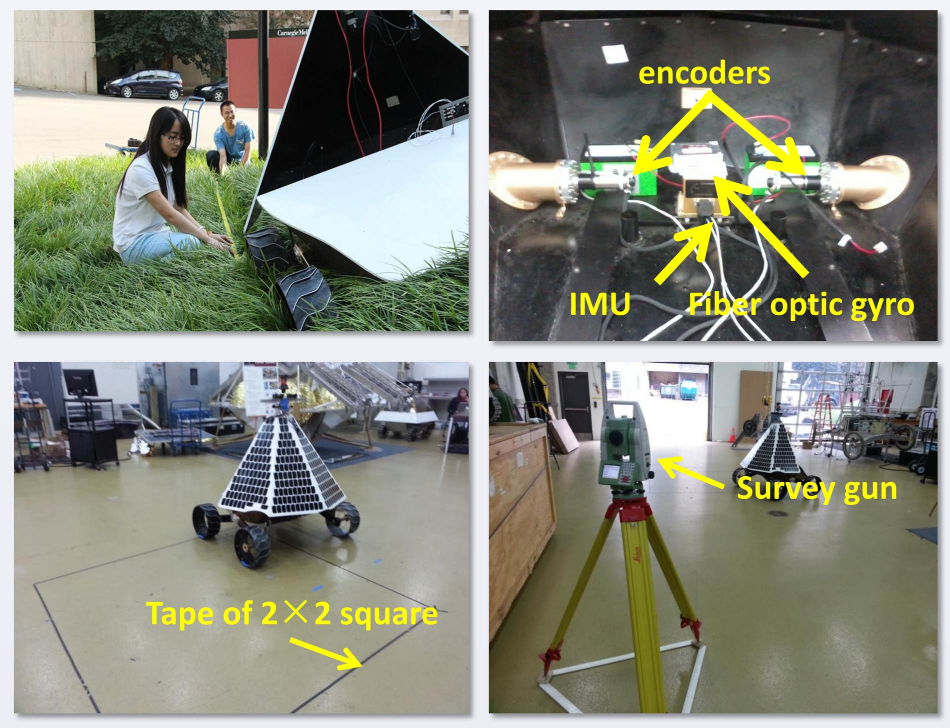
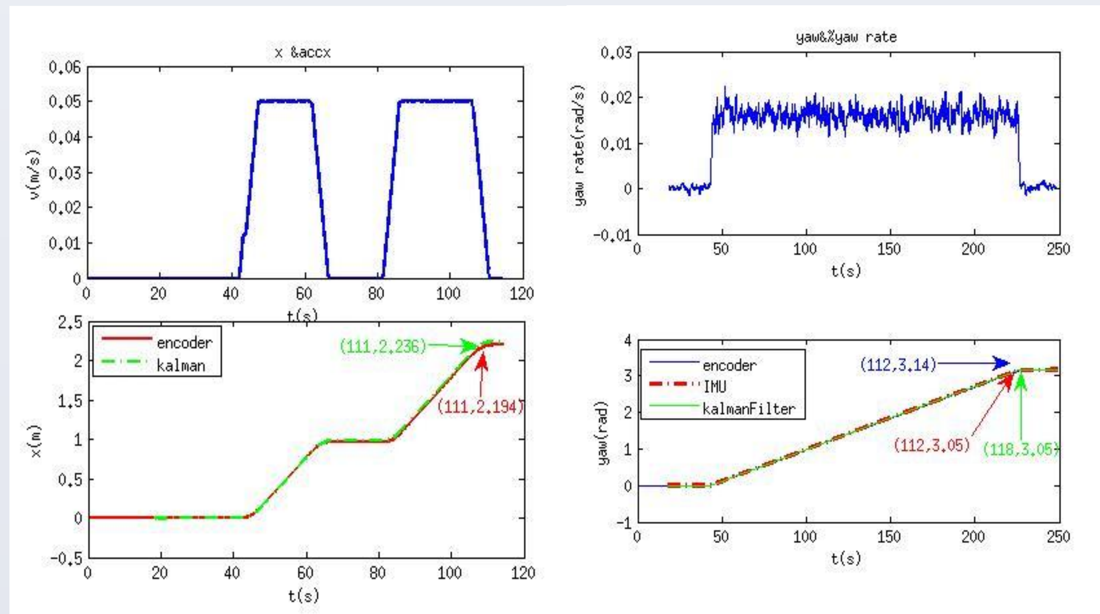


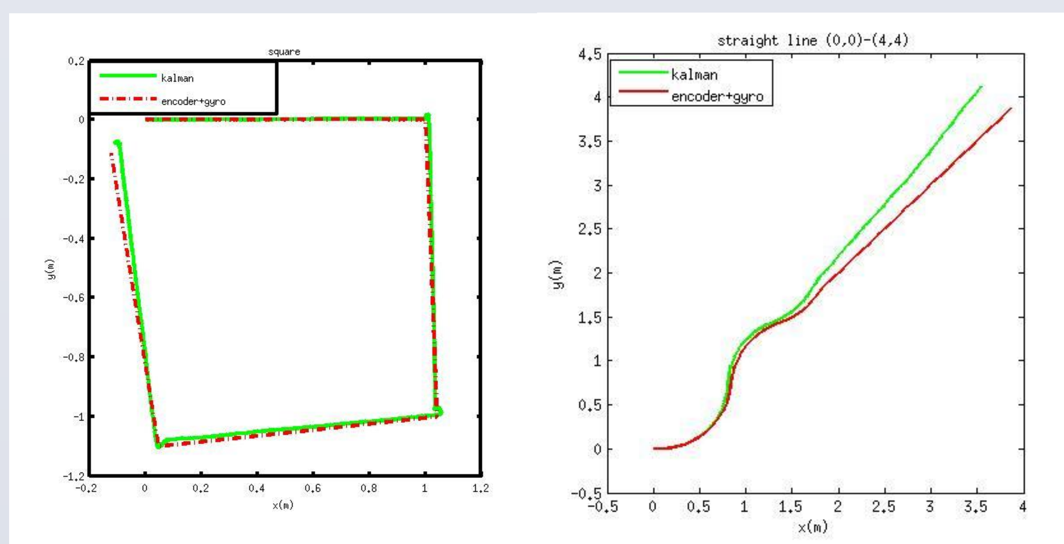
Fig 4. Test environment set-up

Field test results



(a) (b)

Fig 5. forward-stop-forward (a) Pivoting 180 degree(b)



(a) (b)

Fig 6. square (a) straight line using PID control(b)

Figure 5 (a) shows that the Kalman Filter result corresponds to the encoder data when there is little Slip, which also causes doubts that IMU data is just ignored. However, it is clear in figure 6(b) that Kalman filter curve is closer to IMU curve. This explains well that IMU data acts as the prediction source data. Figure 6 depicts the trajectory of prototype 3 walking in a square and in a straight line with a random original heading. The calculated position of the robot drifts over time as the errors in odometry accumulate, mostly from wheel slippage and uneven surfaces. Observations of the position error of p3 reveal that the largest errors are those that accumulate in the theta value: the heading of the robot. Kalman filter effectively decrease those errors.

Future Work

Compare 2D and 3D models

- ◆ The gyros' bias include part of the gravity, which urges a 3D model.
- ◆ The complexity of 3D model will threaten the real time control.

Combine stereo vision in the state estimation

◆ Comparing two differing views on a scene from two horizontally displayed cameras generates depth information.

◆ Feature matching algorithms help reconstruct the 3D world

Employ absolute positioning methods using map matching or satellite signals

References

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2. Mandow.A, Martinez.J.L, Morales.J, Blanco.J.L, "Experimental kinematics for wheeled skid-steer mobile robots", in Proc. of the IEEE Int. Conf. on Intelligent Robots and Systems, San Diego, USA, 2007, pp.1222-1227.

3. Yi.J.G, Zhang.J.J, Song.D.Z, Jayasuriya.S, "IMU-based localization and slip estimation for skid-steered mobile robots", in Proc. of the IEEE Int. Conf. on Intelligent Robots and Systems, San Diego, USA, 2007, pp.2845-2850.

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