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Dead Reckoning for a Lunar Rover on Uneven Terrain

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Abstract

This paper extends the classic dead reckoning approach to the case of a mobile robot moving on uneven terrain such as the lunar surface or a construction site. In addition to the wheel encoders employed in classical odometry, the approach uses accelerometer and gyroscopic sensors, routinely used in aviation but rarely found on contemporary mobile robots. The paper derives a complementary Kalman filter that fuses accelerometer and rate gyro data to increase the accuracy of dead reckoning in uneven terrain. The paper presents empirical demonstrations of the effectiveness of the new method with mobile robot traverses over cratered ground.

1. Introduction

Over the past two years, Carnegie Mellon University has researched and developed rover navigation technologies for lunar robotic exploration [1][2]. In one promising lunar mission scenario, a rover operating under supervisory control will visit certain historic points such as the Apollo 11 and 17 landing sites. For such missions, position estimation is a critical technology; without it, the mission cannot be accomplished.

Numerous position estimation techniques have been reported in the literature. A number of global techniques are applicable to lunar scenarios. For example, it would be possible to identify the rover position with hundred meter accuracy by matching visual landmarks to topographic maps constructed during the recent Clementine mission. However, a rover will encounter local slopes and uneven objects like steps, boulders, and craters, which cannot be known beforehand and some of which cannot be negotiated. Thus, local position estimation is essential for planning and monitoring motion execution in uneven terrain.

Some local position estimation techniques cannot, in principle, work on the Moon. Use of the popular Global Positioning System (GPS) [3][4] is not feasible, since its signals are not readily detectable from the lunar surface. Use of methods involving known environmental maps and external sensing such as radar-beacon systems or sonar [5][6] is not feasible, because such methods assume knowledge about or structure in the environment that is not available. Therefore we consider dead reckoning as an available local position estimation method for our application. (Note that even when GPS or external sensing are available, good dead reckoning could still be necessary for many applications as a supplementary means where these signals are not necessarily reliable, for instance, when the GPS signal can be blocked by tall buildings or degraded by multipath effects).

On the other hand, many research has been conducted about dead reckoning on planer environment using vehicle internal sensing [7][8].

Recently some research has applied inertial navigation systems which are widely used in aviation to outdoor robots for position estimation [9][10][11]. However their application and evaluation of method was for mainly high-speed outdoor vehicle on relatively flat ground. Other interesting research about inertial sensing is to estimate robot attitude on uneven surface (causing just a few degrees body inclination) fusing accelerometer and gyro information [12]. However it was not dedicated for dead reckoning purpose. Thus there seems little application of robot dead reckoning on more uneven terrain like lunar surface before.

The general contribution of the research reported here is to extend the classic dead reckoning approach to the case of a mobile robot which moves on uneven terrain like the lunar surface. The specific contributions are (1) to increase the accuracy of dead reckoning by utilizing robot attitude information (roll and pitch) derived by fusing accelerometer and rate gyro data through a complementary Kalman filter, and (2) to demonstrate and evaluate a preliminary implementation of the approach.

This paper is organized as follows. First, we describe the challenge of dead reckoning on uneven terrain. Next, we describe a dead reckoning method which incorporates vehicle attitude information in addition to wheel rotation and heading information. Then, we describe the result of applying the proposed method to a testbed robot. Finally, we evaluate the proposed method based on the test results.

2. Dead Reckoning on Uneven Terrain

When moving on uneven terrain, the position of a robot changes in three dimensions. Suppose a robot crosses a 30° ridge as shown in Figure 1. If dead reckoning estimates are based exclusively on wheel rotation (for example detected by wheel axle encoders), the robot measures a traverse distance of L in the x direction although the actual traversed distance in x direction is 0.87 L. Thus the dead reckoning error is a 13% overestimate in x position.

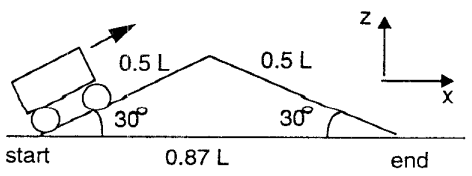


Figure 1: Traverse on 30° ridge

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Incorporating attitude information during such a traverse can improve two-dimensional position estimation accuracy and enable an estimate of motion in the third dimension (z).

Another approach to improving the accuracy of dead reckoning in uneven terrain is to compensate for vehicle-terrain dynamic effects such as wheel slippage, wheel sinkage, and effective wheel radius change due to compressive deformation. These factors tend to yield position estimates which exceed the actual values. For instance, the Apollo Lunar Rover Vehicle overestimated its travel distance by 2-3% on relatively mild lunar terrain [13]. Although these effects are important, to compensate them requires *a priori* knowledge of ground parameters (friction coefficient as a function of wheel slip ratio, soil shear strength, elastic modulus etc.) and a dynamic wheel model. Since it is difficult to measure these parameters *in situ*, they are neglected here in the proposed dead reckoning method.

3. Dead Reckoning Method

In this section, we describe a dead reckoning method that combines attitude and wheel rotation information. Three-axis accelerometers and three-axis rate gyros are used to estimate vehicle attitude. Wheel rotation sensing (e.g., by wheel encoders) is used for estimating incremental vehicle displacement and vehicle velocity. The process, shown in Figure 2, recursively estimates vehicle position.

Velocity

The vehicle velocity v_v in the vehicle coordinate system is calculated from incremental wheel rotations θ_i:

$$v_v(\theta_i) = [v_x, v_y, v_z]^T \quad (i = 1-n) \tag{1}$$

Here n is the number of wheels, and the vehicle coordinate system [x, y, z] is selected so that x is forward, y is lateral and z is vertical up (right-handed). Its origin is located at some point (e.g., the kinematic center) of the robot in (x, y) and on the ground plane in z.

Gravitational acceleration

Accelerometers sense three accelerations (Figure 3):

$$A = a_{ground} + a_{rot} + g \tag{2}$$

Here A represents the accelerometer signals, a_{ground} is the vehicle acceleration at the origin O of the vehicle coordinate system, a_{rot} is the rotational (angular and centrifugal) acceleration which accelerometers sense due to vehicle rotational motion when the accelerometers are located at an offset Δ from O and g is the gravitational acceleration. a_{ground} and a_{rot} are obtained as follows [12]:

$$a_{ground} = \frac{dv_v}{dt} + \omega_v \times v_v \tag{3}$$

$$a_{rot} = \frac{d\omega_v}{dt} \times \delta + \omega_v \times \omega_v \times \delta \tag{4}$$

Here ω_v denotes the vehicle turn rate and can be detected by a three-axis rate gyro. Note that the time derivative of v_v and ω_v is taken with respect to the vehicle frame.

From (1) ~ (4), we obtain g, which implies attitude information, as follows:

$$g = [g_x, g_y, g_z]^T = A - a_{ground} - a_{rot} \tag{5}$$

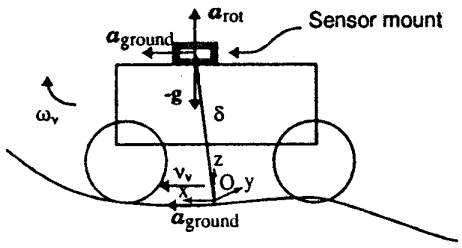


Figure 3: Sensed acceleration at sensor mount

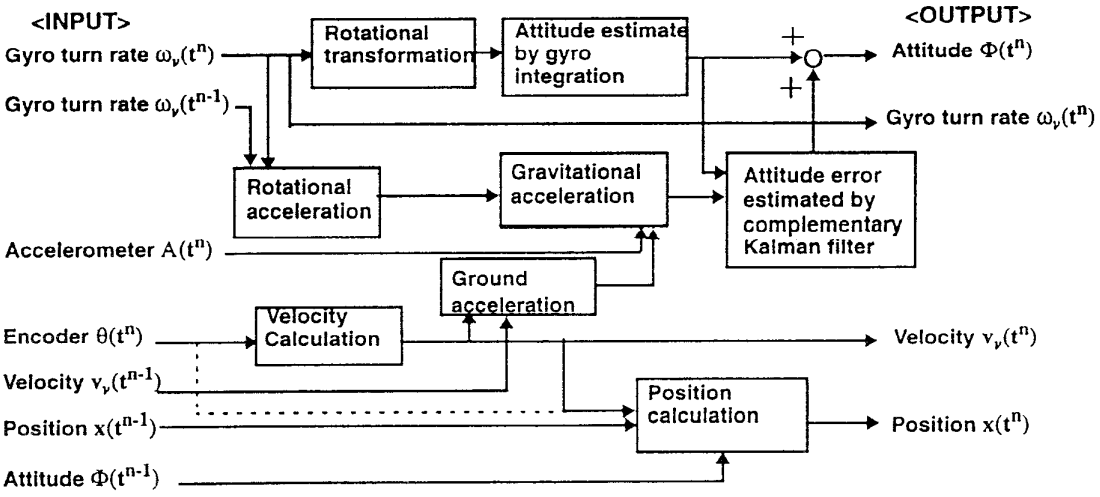


Figure 2: Block diagram of the dead reckoning for a mobile robot

The relationships between gravitational acceleration and vehicle Euler angles are expressed below [12].

$$\Phi_P = -\text{asin}\frac{g_x}{g}$$

$$\Phi_R = \text{asin}\frac{g_y}{g\cos\Phi_P}\left(or\Phi_R = \text{acos}\frac{g_z}{g\cos\Phi_P}\right) \quad (6)$$

Here Φ_R,Φ_P denote vehicle Euler roll and pitch angles, respectively. g denotes the gravitational constant. The order of rotation is roll, pitch, yaw with respect to the ground coordinate system, following the same convention as do aircraft navigation systems.

Attitude estimate from rate gyro integration

The rotational transformation of ω_v into angular velocity in terms of Euler angles ${}^v\Omega = [\dot{\Phi}_R, \dot{\Phi}_P, \dot{\Phi}_Y]^T$ is

$$\Omega = R_I \omega_v \quad (7)$$

Where

$$R_I = \begin{bmatrix} 1 & \sin\Phi_R\tan\Phi_P & \cos\Phi_R\tan\Phi_P \\ 0 & \cos\Phi_R & -\sin\Phi_R \\ 0 & \sec\Phi_P\sin\Phi_R & \sec\Phi_P\cos\Phi_R \end{bmatrix} \quad (8)$$

The Euler angles can be calculated by the time integral of Ω, as follows:

$$\Phi = \int \Omega dt \quad (9)$$

Hence we denote $\Phi^G = [\Phi_P^G, \Phi_R^G]^T$ as the Euler angles estimated from gyroscopic measurement using (7) ~ (9).

Attitude error estimate by complementary Kalman filter

Estimating attitude exclusively from the integrated gyro signals incurs large errors in time due to rate gyro drift. Another source of attitude information is the accelerometers, which can be used to detect vehicle attitude using (1) ~ (6). However they are sensitive to high-frequency vehicle vibration and are thus noisy. A third alternative is to use inclinometers. This option is less attractive because they are normally damped, and thus exhibit relatively slow response.

To address these problems, a Kalman filter has been applied to combine the accelerometer and gyro signals to improve attitude estimation accuracy. A classical Kalman filter approach tends to cause a delayed output due to its low pass filtering nature [9]. To solve this problem, a complementary Kalman filtering method was applied so that accelerometer signal is dominant in low frequency motion while the gyro signal is dominant in high frequency motion [9]. Here the attitude estimate by gyro integration is a reference signal and the Kalman filter estimates the error of gyro drift integration output so that only low-frequency gyro drift effects are corrected (Figure 2). In this way, it does not degrade gyro sensitivity in the high-frequency regime.

A Kalman filter is applied as follows:

State vector: $\hat{x}_k = [d\Phi_P^G, d\Phi_R^G]^T$ (10)

Reference vector: $\bar{x}_{k+1} = \Phi^G$ (11)

Measurement vector: $z_{k+1} = [g_x, g_y, g_z]^T$ (12)

Predictive measurement:

$$h_{k+1} = \begin{bmatrix} -g\sin\Phi_P^G \\ g\cos\Phi_P^G\sin\Phi_R^G \\ g\cos\Phi_P^G\cos\Phi_R^G \end{bmatrix} \quad (13)$$

Measurement matrix: $H_{k+1} = \left.\frac{\partial h_{k+1}}{\partial x_k}\right|_{\bar{x}_{k+1}}$ (14)

State transition model: $\bar{x}_{k+1} = \hat{x}_k$ (15)

State uncertainty covariance transition model:

$$P_{k+1} = \hat{P}_k + Q_k \quad (16)$$

Kalman gain:

$$K_{k+1} = P_{k+1}H_{k+1}^T\left(H_{k+1}P_{k+1}H_{k+1}^T + R_{k+1}\right)^{-1} \quad (17)$$

State uncertainty covariance update:

$$\hat{P}_{k+1} = (I - K_{k+1}H_{k+1})P_{k+1} \quad (18)$$

State update:

$$\hat{x}_{k+1} = \bar{x}_{k+1} + K_{k+1}(z_{k+1} - h_{k+1} - H_{k+1}\bar{x}_{k+1}) \quad (19)$$

In each measurement obtained, the Euler angles can be updated using state update:

$$\Phi' = \Phi^G + \hat{x}_{k+1} \quad (20)$$

In case no reliable ground truth heading sensing is available (as was the case for the test robot in our work), vehicle heading can be obtained using filtered attitude information:

$$\Phi_Y = \int (\omega_y \sec\Phi'_P \sin\Phi'_R + \omega_z \sec\Phi'_P \cos\Phi'_R)\, dt \quad (21)$$

If ground truth heading data is available, it can easily be implemented in the Kalman filter structure.

Position estimate

The incremental traverse distance is obtained by encoders at the vehicle's wheels. The incremental displacement in the ground coordinate system is then obtained as follows:

$$dx = R_2 v_v dt \quad (22)$$

Where R_2 denotes the rotational transformation matrix from the vehicle coordinate system to the ground coordinate system:

$$R_2 = \begin{bmatrix} c\Phi_Y & -s\Phi_Y & 0 \\ s\Phi_Y & c\Phi_Y & 0 \\ 0 & 0 & 1 \end{bmatrix}\begin{bmatrix} c\Phi'_P & 0 & s\Phi'_P \\ 0 & 1 & 0 \\ -s\Phi'_P & 0 & c\Phi'_P \end{bmatrix}\begin{bmatrix} 1 & 0 & 0 \\ 0 & c\Phi'_R & -s\Phi'_R \\ 0 & s\Phi'_R & c\Phi'_R \end{bmatrix} \quad (23)$$

Thus the vehicle position is updated incrementally by

$$x' = x + dx \quad (24)$$

4. Position Estimation Test

Testbed Robot

In order to evaluate the proposed dead reckoning method, it was implemented on the CMU testbed robot Ratler (Figure 4) [1][14]. It has four wheels, each driven by indi-

vidual actuator. The rotational angle of each wheel is detected by an incremental encoder connected co-axially with the motor shaft. Ratler is composed of two bodies connected with a central pivot to allow rotation about the y axis. This unique vehicle design allows conformance to ground roughness, thus enabling higher terrainability. Ratler changes its heading by differentially driving the right and left wheels (skid steering). A sensor mast sits between the two bodies and is connected to the bodies by a motion-averaging four-bar linkage. A strapdown-type Inertial Measuring Unit (IMU) was rigidly attached to a horizontal bar on the mast, so that it can directly measure the camera elevation angle, which is of interest for rover navigation. The IMU, manufactured by Watson industries, contains a three-axis accelerometer, a three-axis gyro, and roll and pitch inclinometers.

Assumption

When the wheels are subject to lateral skidding during turning, the vehicle motion is indeterminate, especially during large turns. The heading estimate generated from differential wheel rotation, which assumes no longitudinal wheel slippage, is not accurate enough to evaluate the effectiveness of the proposed method. Without accurate heading sensing, we limited the scope of experiments to straight-line motion for the purpose of the evaluation of proposed dead reckoning method (although Ratler tended to drift left (+y) when given a straight-line motion command, as will be evident in the test results). The direction of vehicle velocity is assumed to be tangential to the forward (x) direction of the vehicle.

Mast stiffness

Since the IMU was attached to the mast, the stiffness of the mast was important. If the mast is not stiff enough, its deflections due to bending should be modelled to better estimate the attitude of the robot. From the navigation standpoint, it was required to limit the mast deflection angle to 0.1° which corresponds to an error allowance of 1 pixel in the camera image. This requirement is to reduce range data error during stereo image processing. From mast deflection tests, it was found that the addition of the 0.9 kgf IMU caused 0.03° deflection angle during the maximum expected acceleration of 1G, and therefore would not cause significant camera image error during typical rover motion.

Dead reckoning test

To evaluate the proposed method, test runs on various surfaces were conducted. The proposed method (termed "3D estimate") and a conventional dead reckoning method (termed "2D estimate") which assumes no rolling and pitching ($\Phi'_P = \Phi'_R = 0$ in (23)) were compared. Using the 2D estimate, the vehicle heading (yaw angle) was set to be the same as that of the 3D estimate (21) to just monitor the effect of roll and pitch. For each condition, two trials were conducted. Ground truth was measured using a physical protractor and tape measures.

Hard concrete floor

First, to gauge the basic performance of dead reckoning, a hard-floor straight-line test was conducted. Table 1 shows that the dead reckoning accuracy was about 1%. Figure 5 shows percentages of dead reckoning error in the x and y

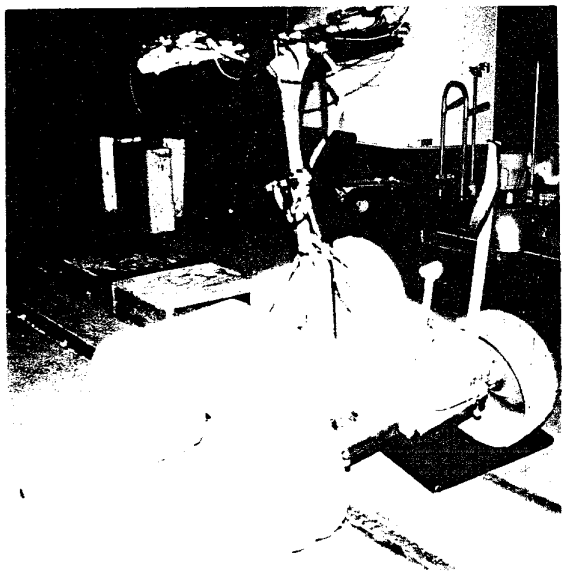


Figure 4: Testbed Robot Ratler

directions over the total traversed distance. In this case, wheel slippage can be found to be negligible. There appears to be no significant difference between the 2D and 3D estimates.

Sandy ground

Second, to assess the effects of a soft material on dead reckoning accuracy, straight-line tests on fairly even sandy surfaces were conducted. In this case, the dead reckoning error was overestimated by 2 to 3% in the x direction (Figure 5). Again, there appears to be no significant difference between the 2D and 3D estimates.

Hard inclined surface

Third, to evaluate the effect of ground inclination, the right wheel of the robot was driven along an inclined surface as shown in Figures 4 and 6, while the left wheels remained on the level floor. The robot rolled and pitched while moving across the surface.

Figure 7 shows the recorded pitch and roll of the robot. The maximum pitch and roll angles of the robot (at the mast) should be 0.085 rad (4.75°) and 0.21rad (11.8°), respectively, based on the geometry of the ramp. The accelerometer signal exhibits high-frequency fluctuation. The integrated gyro signal shows the change in robot attitude, but error accumulates gradually due to gyro drift. The maximum and minimum of the filtered pitch is +0.1 rad (5.7°) and -0.1 rad (-5.7°), respectively, so the error is about 0.015 rad (0.86°), which is attributed to the static accuracy of the accelerometer measurement. The integrated gyro pitch angle shows about 2° error at the end. The filtered attitude converges to nearly zero degrees, thus demonstrating the effectiveness of attitude estimation using the complementary Kalman filter. In this case, the dead reckoning error was about 1% (Figure 5). Despite the body pitching motion, the 2D estimate is still quite good, since the x directional error is less sensitive to pitch angle error as $1 - \cos\Phi_P$, which is only 0.36% when Φ_P is 0.085 rad (4.75°).There appears to be no significant difference between the 2D and 3D estimates.

Cratered sandy ground

Finally, to see the effect of sand and ground unevenness, straight-line tests on sandy crater-like ground were performed (Figure 8). The start and end position of the robot was roughly level. During the run, the robot traversed two craters. The maximum pitch was limited to about 20 degrees. Figure 9 shows the result of both measured and filtered robot attitude. It appears again that the attitude estimate from only the gyro deviates from level at the run end due to drift integration (pitch: 0.7 rad (40.1°), roll: 0.13 rad (7.4°)). However by fusing gyro and accelerometer information, this problem was eliminated so that the filtered attitude resulted in essentially no final error. In this case, the 2D estimate error degrades to 4.4% in the x direction (Figure 4) due to the combined effects of slippage and robot attitude change. In the 3D estimate, dead reckoning error decreased to 3.5% due to the attitude information utilization. The remaining error is thought to be wheel slippage which is dominant in sandy soil.

Table 1: Dead reckoning test result

Ground	Ground truth (X,Y,Z) [m]	3D estimate (X,Y,Z) [m]
Hard concrete floor	(3.909, 0.137,0)	(3.891, 0.159,-0.005)
	(3.986, 0.139,0)	(3.938, 0.123,-0.007)
Sandy ground	(4.782, 0.274,0)	(4.916, 0.239,-0.046)
	(6.632, 0.580,0)	(6.800, 0.601,-0.104)
Hard inclined surface	(5.908, 0.432, 0)	(5.861, 0.489, -0.001)
	(5.571, 0.317, 0)	(5.633, 0.342, 0.038)
Cratered sandy ground	(12.232, 1.543,0)	(12.680, 1.698, 0.217)
	(10.263, 0.539,0)	(10.600, 0.522, 0.357)

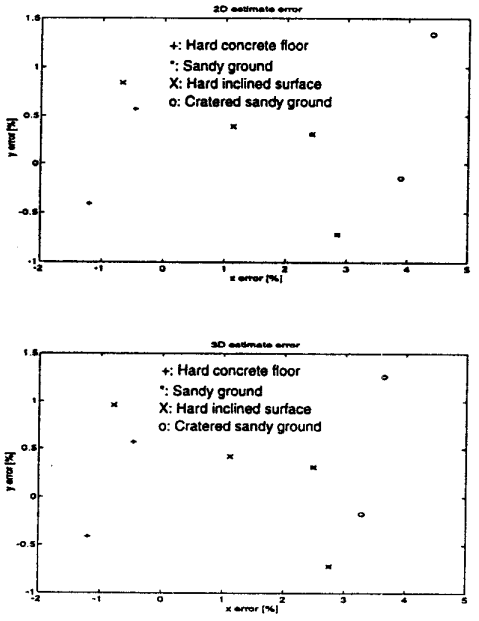


Figure 5: Dead reckoning error in 2D estimate and 3D estimate

5. Discussion

In the dead reckoning test on a sandy cratered surface, the 3D dead reckoning estimate exhibited only a 1% accuracy improvement when compared to the 2D estimate. However for steeper craters or steps where robot attitude changes are large, the improvement from the 3D estimate will increase. On soft surfaces, the dominant error source proved to be wheel slippage (2 ~ 3%). We believe it could be reduced by incorporating another speed measurement device such as an additional small free wheel or optical flow measurement by side cameras. Note that the elevation error (z) (Table 1) is relatively large due to its sinusoidal dependance on pitch measurement error (e.g. 1.8 ~ 3.5% in sandy cratered ground). The dead reckoning method described here could also be applied to terrestrial vehicles operating on uneven terrain such as a construction site. However, in practice, its application is limited to short distance local position estimation [10]. Exploiting its

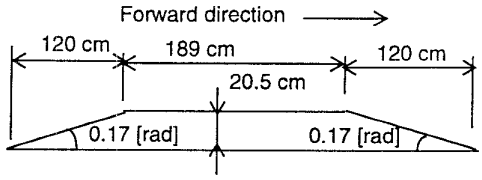


Figure 6: Hard inclined surface for test

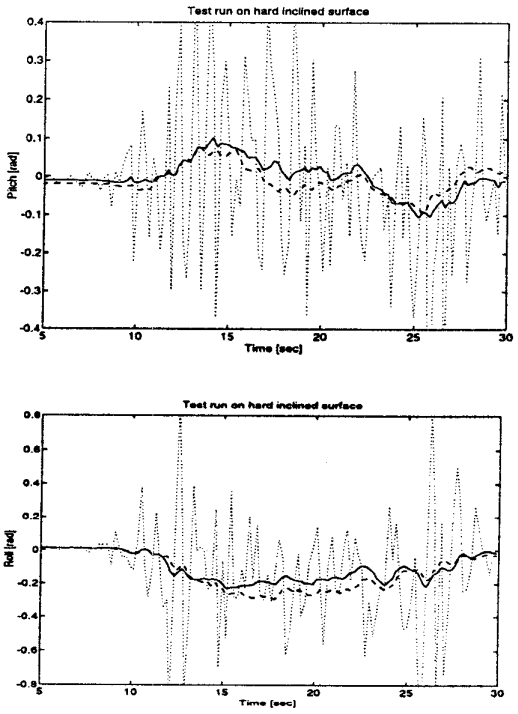


Figure 7: Robot attitude on hard inclined surface

real-time position measuring capability would be useful as a supplementary measurement means for global navigation (visual landmark matching, GPS) when those sensing methods are not necessarily reliable (e.g., when a GPS signal is blocked by a building) or when position estimation frequency is too low.

6. Conclusion

(1) A attitude estimation method fusing accelerometer and gyroscope information with a complementary Kalman filter was proposed. The accuracy of the filtered attitude was found to be about 1°. This could be reduced by improving the static accuracy of the accelerometer measurements.

(2) Dead reckoning of a mobile robot for uneven terrain was developed to utilize robot attitude information obtained by (1).

(3) Dead reckoning tests on cratered ground showed the effectiveness of the new method in reducing error and improving dead reckoning accuracy.

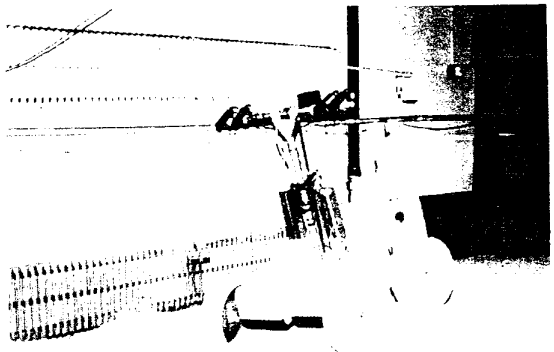


Figure 8: Test run on sandy crater

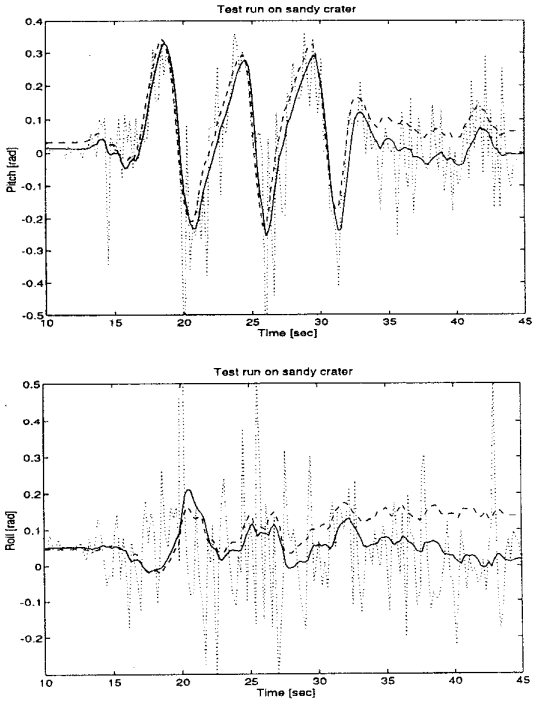


Figure 9: Robot attitude on sandy crater run (Each plot is same as Figure 7)

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