The University of Michigan

Improved Position Estimation for Mobile Robots on Rough Terrain Using Attitude Information

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By
Lauro Ojeda and Johann Borenstein
Department of Mechanical Engineering

ABSTRACT

Most mobile robots use a combination of absolute and relative sensing techniques for position estimation. Relative positioning techniques are generally known as dead-reckoning. Many systems use odometry as their only dead-reckoning means. However, in recent years fiber optic gyroscopes have become more affordable and are being used on many platforms to supplement odometry, especially in indoor applications. Still, if the terrain is not level (i.e., rugged or rolling terrain), the tilt of the vehicle introduces errors into the conversion of gyro readings to vehicle heading. In order to overcome this problem vehicle tilt must be measured and factored into the heading computation.

This technical report introduces a new fuzzy logic expert rule-based method for fusing data from multiple low- to medium-cost gyroscopes and accelerometers in order to estimate accurately the attitude (i.e., heading and tilt) of a mobile robot. The attitude information is then further fused with wheel encoder data to estimate the three-dimensional position of the mobile robot. Experimental results of mobile robot runs over rugged terrain are presented, showing the effectiveness of our fuzzy logic rule-based sensor fusion method.

1. INTRODUCTION

Most mobile robots estimate their position through a combination of absolute and relative sensor systems. Absolute sensor systems are those that rely on external beacons or landmarks, such as GPS and natural or artificial landmarks in the environment [Borenstein et al., 1996]. Relative positioning sensors are those that don't use clues from the environment, such as wheel encoders for odometry and inertial sensors. Navigation based on relative positioning, also called dead-reckoning, is the subject of this technical report.

It is generally unfeasible to use only dead-reckoning in a mobile robot, because relative positioning accumulates errors over time and/or distance, and these errors grow without bound. Absolute positioning alone is also unfeasible in most situations, because the external beacons or markers are not necessarily available everywhere along the vehicle's path. This is particularly true in GPS-based outdoor systems, where dense foliage or tall nearby structures (the so-called "urban canyon") may obstruct the "view" of the sky of the receiver. It is therefore widely accepted practice to combine absolute and relative positioning, and experts agree that improved dead-reckoning increases the distance and/or time over which a mobile robot can operate without absolute position updates.

The most popular and easy-to-implement means of dead-reckoning is odometry. However, this method introduces substantial, unbounded errors when traveling over irregularities on the ground. On rugged outdoor terrain it is therefore not feasible to use odometry as the only means for dead-reckoning.

In recent years fiber optic gyroscopes have become very affordable, and in many mobile robots odometry and fiber optic gyroscope are combined, resulting in dramatically improved dead-reckoning accuracy. One problem, however, is that a single gyro is effective only on planar terrain. However, when used on rugged or rolling outdoor terrain, a single gyro will not suffice to measure accurately the change of heading of a vehicle if it turns on an incline. This is so because the sensitive axis of the vehicle-mounted gyro remains normal to the plane of the vehicle, but not parallel to the z-axis of the world coordinate system, in which the heading angle is measured. A discussion on this issue and a definition of terms is presented in Section 2.

For accurate computation of the heading of a platform it is therefore necessary to know the deviation of the platform from the horizontal plane. We will explain in Section 3 that this information, also known as "tilt," is best obtained from a three-axis gyro systems (with some other enhancements, also explained in Section 3).

While three-axes gyros are commercially available, high-quality units typically cost over \$10,000. Because this cost is inhibitive for most mobile robot applications we have developed a three-axes gyro system that measures tilt with one low-cost, two-axes Corriolis gyro (costing ~\$150) in conjunction with low-cost accelerometers. A single high-quality fiber optic gyro (costing ~\$2,000) is still used to measure the robot's turning rate (i.e., the rotation about the platform's z-axis).

We also introduce in this technical report a novel <u>F</u>uzzy <u>L</u>ogic and <u>Ex</u>pert rule-based <u>nav</u>igation method (FLEXnav) to fusing the data from these different sensor modalities. Unlike the commonly used Kalman filter techniques for fusing sensor data [Tonouchi, et al., 1994; Krantz and Gini, 1996], our system is based on expert rules derived from careful observations of the physical functioning of each sensor. Our basic philosophy is that many error mechanisms can be defined more specifically and accurately by expert reasoning, based on in-depth physical understanding of sensors and their associated error sources, than by the statistics-based Kalman Filter methods [Chung et al., 2001]. Our FLEXnav approach is explained in detail in Section 4. Section 5 briefly explains how to estimate position based on odometry and the heading estimations, and Section 6 presents experimental results, including actual robot runs over very rugged terrain.

2. Attitude Estimation

The angular attitude of a robot is a set of three angles measured between the robot's body and the absolute world coordinate system. Sometimes the term "navigation frame" is used for a world coordinate system, in which the x axis points east, the y axis points north, and the z axis is parallel but opposite in sign to the local gravity vector. Another coordinate system, called

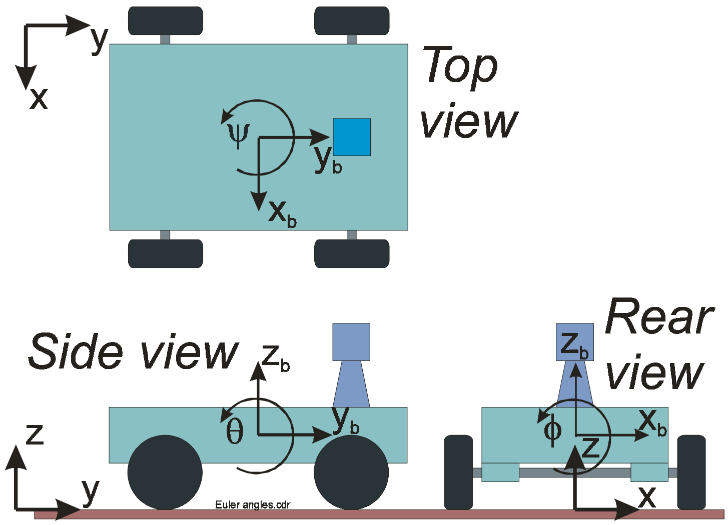

Figure 1: Robot axes and Euler angles (adopted from [Kelly, 1995])

"body frame" can be considered embedded in the robot body so that its x-axis points to the right, the y-axis points forward, and the z-axis points upward. Body axes are labeled x_b, y_b, and z_b [Kelly et al., 1995], and the accelerometers and gyroscopes described in this technical report were mounted in alignment with these axes. Three angles express the relative orientation between the body frame and the navigation frame, as shown in Figure 1.

The most common form of representation for these three angles is the so-called set of *Euler angles,* ϕ, θ, and ψ. These three angles are called *roll* (sometimes also called "bank angle"), *pitch* (also called "elevation"), and *yaw* (also called "heading" or "azimuth"), respectively. ϕ Is the angle between x_b and the horizontal plane (i.e., the plane that is normal to the z axis of the navigation frame), θ is the angle between y_b and the horizontal plane, and ψ is the angle between x and the projection of x_b on the horizontal plane [Biezad et al., 1999]. For the mathematical treatment in the following sections we define a vector $\Lambda = [\phi, \theta, \psi]^T$ that will represent the Euler angles throughout this technical report.

Rates of rotation of the body frame relative to the navigation frame can be expressed in terms of the derivatives of the Euler angles, called "*Euler rates*."

Specifically, Euler rates Ω_ε and body rates of rotation Ω_b are related by:

$$\Omega_\varepsilon = \begin{bmatrix} \dot{\theta} & \dot{\phi} & \dot{\psi} \end{bmatrix}^T = C_b^\varepsilon \Omega_b \tag{1}$$

Where

$$C_b^\varepsilon = \begin{bmatrix} 1 & \sin\phi \tan\theta & \cos\phi \tan\theta \\ 0 & \cos\phi & -\sin\phi \\ 0 & \dfrac{\sin\phi}{\cos\theta} & \dfrac{\cos\phi}{\cos\theta} \end{bmatrix}$$

$$\Omega_b = \begin{bmatrix} \omega_x & \omega_y & \omega_z \end{bmatrix}^T$$

ω_x, ω_y, and ω_z are the rates of rotation of the vehicle around the respective axes of the body frame.

Euler angles can be calculated from Euler rates by integrating Ω_ε over time:

$$\Lambda = [\theta \quad \phi \quad \psi]^T = \int \Omega_\varepsilon dt \tag{2}$$

For many indoor mobile robotics applications, where floors are typically level, it is an acceptable and widely used assumption that ϕ and θ can be considered to equal zero. With this assumption we can rewrite Eq. (1):

$$\dot{\psi} = \omega_z \tag{3}$$

According to Eq. (3) the heading angle ψ can be estimated by integrating only ω_Z.

However, on rough terrain or when position estimation in three dimensions (3D) is required, all three attitude parameters must be considered. In the next section we introduce our low-cost sensing system for measuring all three attitude parameters.

3. Attitude Estimation Sensors

Attitude relative to the horizontal plane xy (i.e., roll and pitch – ϕ and θ, respectively) is often referred to as "*tilt.*" Low cost tilt sensors are commercially available, typically in the form of electrolytic fluid sensors. However, most of these sensors are suitable only for static or quasi-static conditions because of their slow response time. In other words, they are suitable only for operation on gently rolling terrain. For operation on rugged terrain faster tilt sensors are required.

Tilt can also be measured with magnetometers, but this approach is not suitable for indoor applications, where locally strong fluctuations in magnetic fields are introduced by electric power lines, metal structures, or other electromagnetic sources. Yet another approach is based on measuring tilt with accelerometers, although the problem here is the high drift rate of these sensors [Merhav, et al., 1996].

For dynamic applications requiring all three attitude parameters the conventional approach has been based on integration of rate information from sets of three mutually perpendicular gyroscopes. Three-axis gyroscopes are commercially available but aimed primarily at use in aircraft or missiles. Such systems, although typically more accurate than the system described here, are also prohibitively expensive for most mobile robot applications.

In this technical report we described an approach that aims at using lower-cost sensing components while still providing high accuracy. We compensate for the relative poor performance of these low-cost components by taking into account the particularities of mobile robot navigation on rugged terrain. Some of these particularities are:

1. The mobile robot is horizontal, near horizontal or at constant tilt, most of the time.
2. Mobile robot velocities and accelerations are small – orders of magnitude lower than those of missiles or aircraft.
3. Wheeled and even tracked vehicles allow for the use of odometry – an advantage entirely absent in aircraft or watercraft.

In our system we used one accurate (but more costly) fiber-optic gyroscope, and two low-cost but inaccurate Coriolis gyros. In addition we used two low-cost accelerometers.

The accurate gyro is a fiber optic gyro model RA2100 made by [KVH]. In earlier work we developed a precision calibration system for this gyro, which reduces the errors due to the non-linearity of the scale factor and temperature by about one order of magnitude compared to an off-the-shelf unit [Ojeda et al., 2000].

We use this rather accurate, calibrated gyro to measure the heading angle ψ, which, according to assumption (1) above, is the most important angle for land vehicles and is affected mostly by ω_z (see Eq. 1). To measure the less important angular rates ω_x and ω_y, we used a low cost two-axes Coriolis-based gyroscope made by [GYRATION]. Again under assumption (1) these angular speeds will affect primarily ϕ and θ. The low-cost Coriolis gyroscopes have significant limitations, such as large drift errors, noisy output, inaccuracy, sensitivity to acceleration, etc. The most severe limitation of the Coriolis gyros is the large drift rate. However, as was shown by Borenstein and Feng [1996], one can overcome this limitation by using the gyro readings only during carefully selected, short periods of time.

We also incorporated two low-cost accelerometers [ANALOG DEVICES] along the x_r and y_r axes to estimate tilt information ϕ and θ when the robot is static or moving linearly at constant speed. Under these conditions tilt can be calculated as follows:

$$\phi = \sin^{-1}\left(\frac{g_x}{g}\right) \tag{4}$$

$$\theta = \sin^{-1}\left(\frac{g_y}{g}\right) \tag{5}$$

where

g — gravitational acceleration

g_x — x-component of the gravitational acceleration.

g_y — y-component of the gravitational acceleration

Similar to gyroscopes, accelerometers suffer from bias drift problems. It is well established that accelerometers are generally not suitable for measuring linear displacement in mobile robots [Barshan and Durrant-Whyte, 1995]. This is because accelerometer measurements must be integrated twice to yield position, and thus even small amounts of drift will grow substantially and without bound. However accelerometers can be used as tilt sensors since tilt information can be derived directly form the accelerometer readings (see Eqs. 4 and 5). No integration is needed and therefore drift is not a dominant source of errors. Rather, other sources of error become relatively more significant, such as: inaccuracy, noise, non-linearity, and sensitivity to vibration. Nonetheless, accelerometers can be useful to bound and reset the tilt information calculated by the gyroscopes. A block diagram of the complete system is shown in Figure 2, and a photograph is shown in Figure 3). It should be emphasized that it is critically important to mount the sensors in proper alignment.

Under dynamic conditions, i.e., when the robot accelerates, accelerometers will also measure the acceleration of the robot in addition to the robot's tilt. Such ambiguity can be resolved using encoder readings.

4. FUZZY MULTI-SENSOR DATA FUSION USING EXPERT RULES

Based on the specific physical shortcomings and strengths of each sensor modality, we have defined the following basic expert rules:

Rule 1:

If the vehicle is in the process of turning about any of its axes, our best attitude estimate is the one derived from the gyroscope outputs, that is $\Lambda \approx \Lambda_g$, where

$$\Lambda_g = [\theta_g \quad \phi_g \quad \psi_g]^T \tag{6}$$

and the index 'g' indicates that the value was derived from gyro data. θ_g, ϕ_g, and ψ_g are computed from gyro data according to equations (1) and (2).

Rule 2:

If the robot is not turning around any axis and not accelerating linearly, the accelerometers can directly measure the roll and pitch attitude parameters (ϕ_a and θ_a). If the conditions of Rule 2 are met for several seconds uninterruptedly, then we can also measure and correct for the bias drift errors of the gyroscope (see [Ojeda et al., 2000]) and reset the tilt parameters of the robot to the tilt estimated by the accelerometers (see Eqs. 4 an 5), therefore

$$\phi \approx \phi_a \text{ and } \theta \approx \theta_a \tag{7}$$

In both cases the symbol "≈" means "*tendency*" instead of "equality."

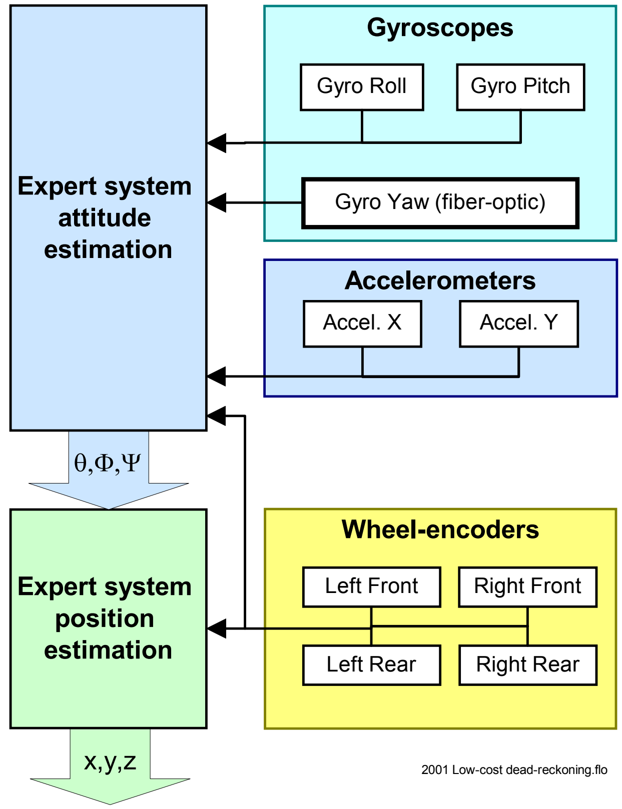

Figure 2: Block diagram of our low-cost 3D position estimation system for mobile robots.

Figure 3: The inertial components of the attitude measuring system: KVH fiber-optics gyroscope, Gyration two-axes Coriolis gyroscope and an Analog Devices two-axis accelerometer.

Even though the sensor integration conditions are well defined and sensible, it is not feasible to implement them as strictly binary rules. This is due to the natural imprecision of the sensors and because conditions like "robot not turning" or "constant speed" are not realistic when the vehicle is in motion on rugged terrain.

An integration algorithm that takes into account the physical capabilities and limitations of each sensor is therefore necessary. We found that fuzzy logic is well suited for this task.

- Fuzzy logic uses rules to map inputs and outputs. Using natural language, expert rules as the ones described above can be translated easily into IF-THEN statements used by fuzzy logic rules. This feature was especially important to incorporate the fusion conditions into the system.

- Fuzzy logic is specifically designed to deal with the imprecision associated with the noisy low-cost sensors used in our system.
- Trying to use a deterministic approach to solve this kind of problem accurately would require the development of a highly non-linear system model, which, in turn, would increase the complexity and development time. Fuzzy logic, on the other hand, can handle nonlinear models of arbitrary complexity [Sang et al., 1997].

Our fuzzy data fusion uses four fuzzy membership functions[1] inputs and two outputs (see Figure 4). The first input represents the state of rotation (i.e., whether the platform is rotating about any axis). The parameter that determine this condition is calculated by:

$$\omega_t = |\omega_x| + |\omega_y| + |\omega_z| \tag{8}$$

The second and third inputs will determine whether or not the acceleration of the robot is changing as seen by the accelerometers, which would suggest that the robot is rotating, or accelerating (see Eqs. 9 and 10):

$$\Delta a_x = a_x[n] - a_x[n-1] \tag{9}$$

$$\Delta a_y = a_y[n] - a_y[n-1] \tag{10}$$

If $\Delta a_x \approx 0$ and $\Delta a_y \approx 0$ then this means that the robot is either standing or moving with constant acceleration, and that it is standing or moving on terrain that has a constant slope. The "standing-or-moving" ambiguity can be resolved using encoder information, which is the fourth input to the system. The first derivative of the velocity as measured by the encoders represents the acceleration of the robot (see Eq. 11).

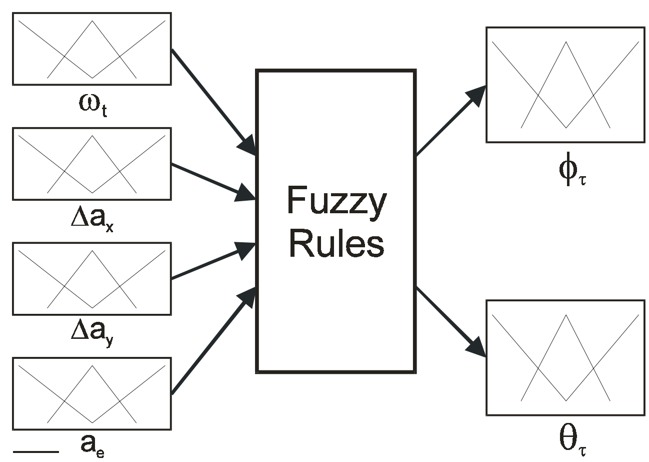

Figure 4: Inputs and outputs of the fuzzy multi-sensor data fusion system.

$$a_e = \Delta v_e = v_e[n] - v_e[n-1] \tag{11}$$

The outputs of the fuzzy fusion system, ϕ_τ and θ_τ, are dimensionless weighting factors that emphasize either the gyroscope readings, the accelerometer readings, or both of them. In practice these weighing factors can range from 0 to 1 and are used as follows.

$$\phi = \phi_g + (\phi_a - \phi_g)\phi_\tau \tag{12}$$

$$\theta = \phi_g + (\theta_a - \theta_g)\theta_\tau \tag{13}$$

Once the inputs and outputs are identified and defined, one needs to establish the relationship between them. As mentioned above, fuzzy logic uses IF-THEN rules to map inputs and outputs. For our fuzzy logic fusion system we translated our knowledge base (fusion rules) into the fuzzy rules shown below:

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[1] In Fuzzy Logic, a "membership function" is defined as a curve that maps each point in the input space to a membership value or grade between 0 and 1.

$\Re_1$: ***if*** ω_t is not SLOW ***then*** ϕ_τ is GYRO ***and*** θ_τ is GYRO
$\Re_2$: ***if*** Δa_x is HIGH ***then*** ϕ_τ is GYRO
$\Re_3$: ***if*** Δa_y is HIGH ***then*** θ_τ is GYRO
$\Re_4$: ***if*** a_e is HIGH ***then*** ϕ_τ is GYRO ***and*** θ_τ is GYRO
$\Re_5$: ***if*** ω_t is SLOW ***and*** Δa_x is LOW ***and*** a_e is LOW ***then*** ϕ_τ is ACCEL
$\Re_6$: ***if*** ω_t is SLOW ***and*** Δa_y is LOW ***and*** a_e is LOW ***then*** θ_τ is ACCEL
$\Re_7$: ***if*** ω_t is SLOW ***and*** Δa_x is LOW ***and*** a_e is MED ***then*** ϕ_τ is BOTH
$\Re_8$: ***if*** ω_t is SLOW ***and*** Δa_y is LOW ***and*** a_e is MED ***then*** θ_τ is BOTH
$\Re_9$: ***if*** ω_t is SLOW ***and*** Δa_x is MED ***and*** a_e is LOW ***then*** ϕ_τ is BOTH
$\Re_{10}$: ***if*** ω_t is SLOW ***and*** Δa_y is MED ***and*** a_e is LOW ***then*** θ_τ is BOTH
$\Re_{11}$: ***if*** ω_t is MED ***and*** Δa_x is LOW ***and*** a_e is LOW ***then*** ϕ_τ is BOTH
$\Re_{12}$: ***if*** ω_t is MED ***and*** Δa_y is LOW ***and*** a_e is LOW ***then*** θ_τ is BOTH
$\Re_{13}$: ***if*** ω_t is MED ***and*** Δa_x is not LOW ***then*** ϕ_τ is GYRO
$\Re_{14}$: ***if*** ω_t is MED ***and*** Δa_y is not LOW ***then*** θ_τ is GYRO
$\Re_{15}$: ***if*** ω_t is MED ***and*** a_e is not LOW ***then*** ϕ_τ is GYRO ***and*** θ_τ is GYRO

Figure 5 shows the membership functions used as input and output of our system, and Figure 6 shows how the ϕ_τ output of the expert system relates to some specific input conditions. Similar relationships were derived for θ_τ.

It should be noted that the FLEXnav system described in this technical report is only used to reduce errors in roll and pitch (ϕ and θ, respectively), which would otherwise be very large because neither the accelerometers nor the low-cost gyros by themselves are very accurate. And since roll and pitch affect the computation of the heading angle ψ (as shown in Eq. 1, for rugged terrain), reducing the errors in roll and pitch reduces the errors in ψ. The experimental results in Section 6 substantiate this claim.

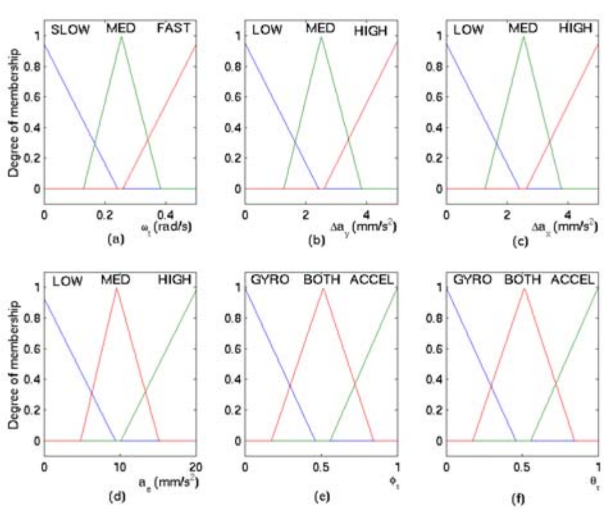


Figure 5: Membership functions of the fuzzy fusion algorithm: a), b), c) and d) are inputs; e) and f) are outputs

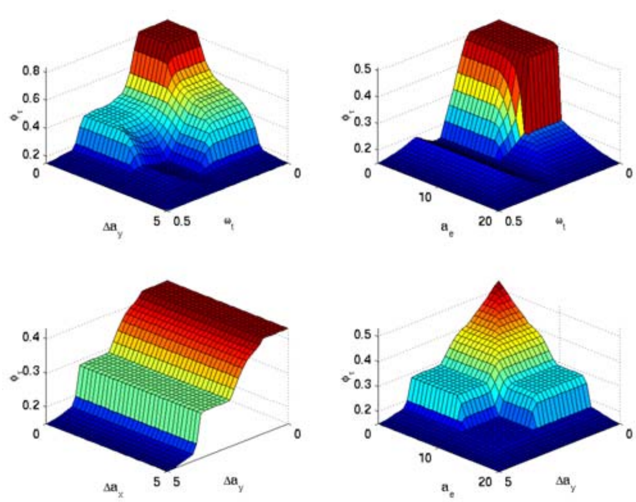


Figure 6: Relationships between the four inputs and one of the two outputs, ϕ_τ.

5. POSITION ESTIMATION

Once attitude has been calculated, the next step is to use this information to estimate the position of the robot with respect to the navigation frame, denoted as $P = [x \quad y \quad z]$. Our dead reckoning system uses only wheel encoder information as a means of measuring the linear movement of the robot, which means that we can only sense the motion of the robot along the y_r robot axis. We will denote the linear displacement of the robot along its longitudinal axis Δy_r. Therefore any other kind of movement will not be detected or considered in the solution. In other words

$\Delta x_r = 0$ sideways movement

$\Delta z_r = 0$ vertical movement

Under these conditions, the estimation of the instantaneous linear movement of the robot with respect to the navigation frame can be calculated as follows:

$$\Delta P = [\Delta x, \Delta y, \Delta z] = \Delta y_r[\cos\theta \cos\psi, \cos\theta \sin\psi, \sin\theta] \quad (14)$$

At any instant n, the position of the robot can be expressed as:

$$P_n = [x_n, y_n, z_n] = P_{n-1} + \Delta P \quad (15)$$

6. EXPERIMENTAL RESULTS

We performed several experiments to test our multi-sensor data fusion algorithm on rugged terrain. The mobile platform used in all experiments was a Pioneer AT 4-wheel drive/skid-steer mobile robot, shown in Figure 7. The robot was remotely controlled to drive along a closed loop path so that at the end of each run it returned to the initial position. The total path length was about 100 m and the duration of each trip was about 98 sec. Thus, the platform's average speed was about 1 m/sec. During each experiment all the sensor signals where recorded for posterior analysis.

The experiments were performed on sloped and gently rolling lawn. Bark, heaped up highly around large trees on the lawn provided for somewhat steep moguls, as shown in Figure 8. The remote operator took particular care to make the Pioneer turn right on those moguls, as these slopes were expected to introduce the largest errors. As a result, the trajectories looked irregular, as shown in Figure 9.

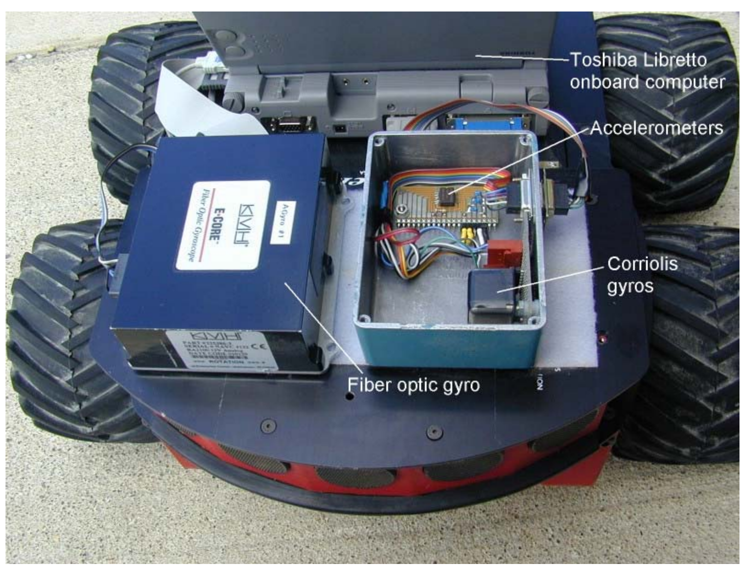


Figure 7: This Pioneer AT was used in all of the experiments.

Figure 8: Partial view of the terrain on which the experiments were run. Moguls with up to 10-degree slopes were created by the piles of bark surrounding the trees.

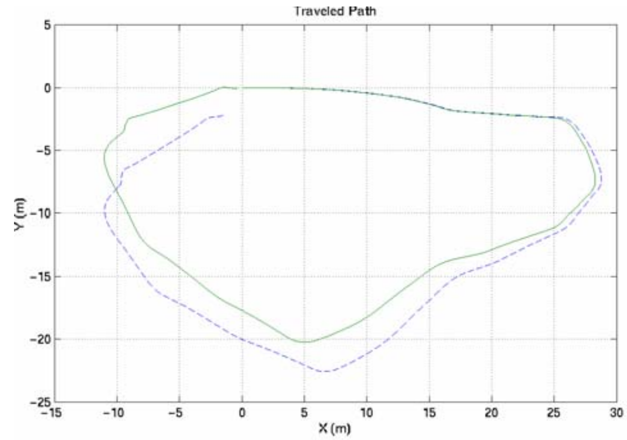
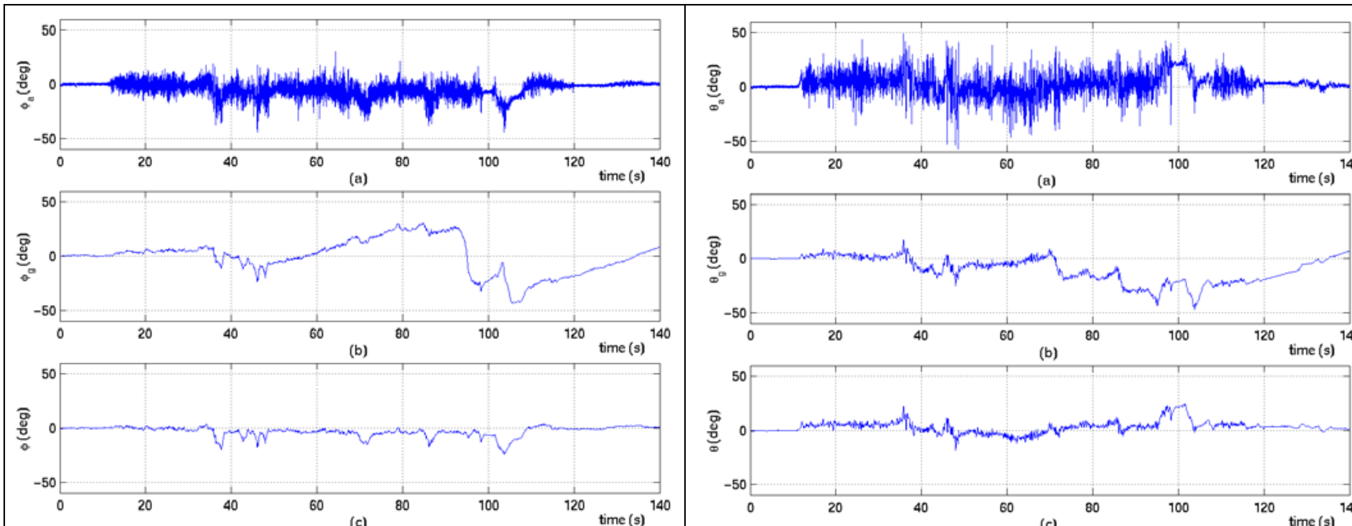


Figure 9: Robot traveled path, dashed lien shows the path of the robot estimated using only a fiber optics gyroscope on the Z axis, solid line is the estimated path of the robot as seen by our FLEXnav system

6.1 Experimental results for the heading angle

We ran the robot several times approximately along the above described path. A set of roll and pitch angles computed only from readings from the accelerometers and Coriolis gyroscopes are shown in Figure 10a and Figure 10b for a typical run. Figure 10c show the roll and pitch angles after fusing the accelerometer and Coriolis gyro data with our FLEXnav method .



Roll angle ϕ

Pitch angle θ

Figure 10: Roll angle (left pane) and pitch angle (right pane) of the robot as measured by a) the accelerometers, and b) the Coriolis gyroscopes. c) Roll angle ϕ and pitch angle θ as computed after merging accelerometer, gyroscope, and odometry data with our FLEXnav system.

Table I: Absolute return heading errors after returning to the starting position for a total of eight runs along the path of Figure 9.

Run #	Absolute Heading Error (in degrees), after correcting the fiber optic gyro data (heading) with tilt data from			
	No tilt data used in heading calculation	Coriolis gyros tilt data only	Accelerometers' tilt data only	Coriolis gyros and accelerometers, fused with FLEXnav
1 (cw)	7.5	9.2	21.8	0.3
2 (cw)	18.2	6.5	21.3	1.9
3 (cw)	5.2	6.2	29.7	0.8
4 (cw)	12.0	13.6	14.3	1.5
5 (ccw)	5.7	7.9	15.2	1.9
6 (ccw)	6.8	20.8	12.2	0.8
7 (ccw)	15.0	1.3	6.5	1.1
8 (ccw)	4.5	10.3	9.1	0.7
Average	9.4	9.4	16.3	1.1

Once the momentary tilt of the platform is computed (i.e., the data plotted in Figure 10c), the heading angle ψ can be computed using Eqs. (1) and (2) and the data from the high-quality fiber-optic gyroscope. Since in our experiments there was no way to measure the absolute attitude of the robot at any given time, we can compare in our experimental results only the final, computed pose (i.e., position and heading) with the actual pose of the robot. We recall that the robot was steered so that its final pose coincided with its starting pose.

We performed a total of four runs in clockwise (cw) and four runs in counter-clockwise (ccw) direction. The resulting absolute heading errors after returning to the starting position were measured and are shown in Table I and Figure 11 for four different sensing configurations: a) with only the fiber optic gyro that measured heading (i.e., without any, tilt information); with tilt information based (b) only on the Coriolis gyros; (c) only on the accelerometers; or (d) on the FLEXnav system (Coriolis gyros and accelerometers). The results show that the FLEXnav system improves heading measurement accuracy by about one order of magnitude over the other three options. Figure 11 shows a plot of the difference between the momentary heading angles as computed by the fiber optic gyro only and by the fiber optic gyro with FLEXnav-derived tilt data, for one of the runs. If we assume for a moment (as is supported by the low return heading errors in Table I) that the heading computed with FLEXnav-derived tilt data is almost absolutely correct, then Figure 11 shows how the heading error in the case of the fiber optic gyro-only (without tilt data) would accumulate on rugged terrain.

6.2 Experimental results for position estimation

From Equation 12 and 13 it is clear that an attitude estimation error will be reflected in the positioning estimation, and that this error will increase over time. The final positioning error for the experiments explained in Section 6.1 are shown in Figure 13.

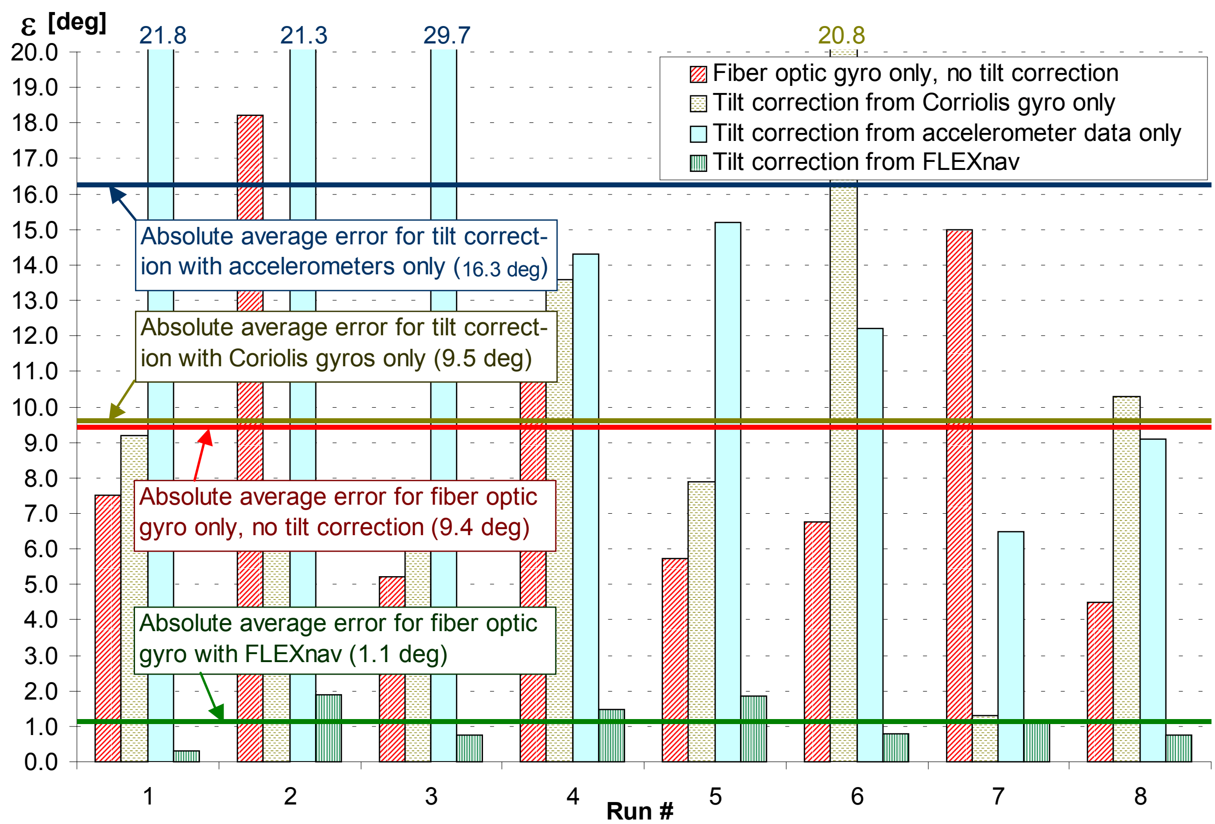


Figure 12: Absolute return orientation errors after completing the 100 m run over rugged terrain.

In addition to the corrections of the final position estimation, our system can provide an estimate on the third position coordinate, z. In a different set of our experiments we ran the robot over an elevated plateau (see Figure 14a) and our system correctly estimated the contour of this plateau, as shown in Figure 14b.

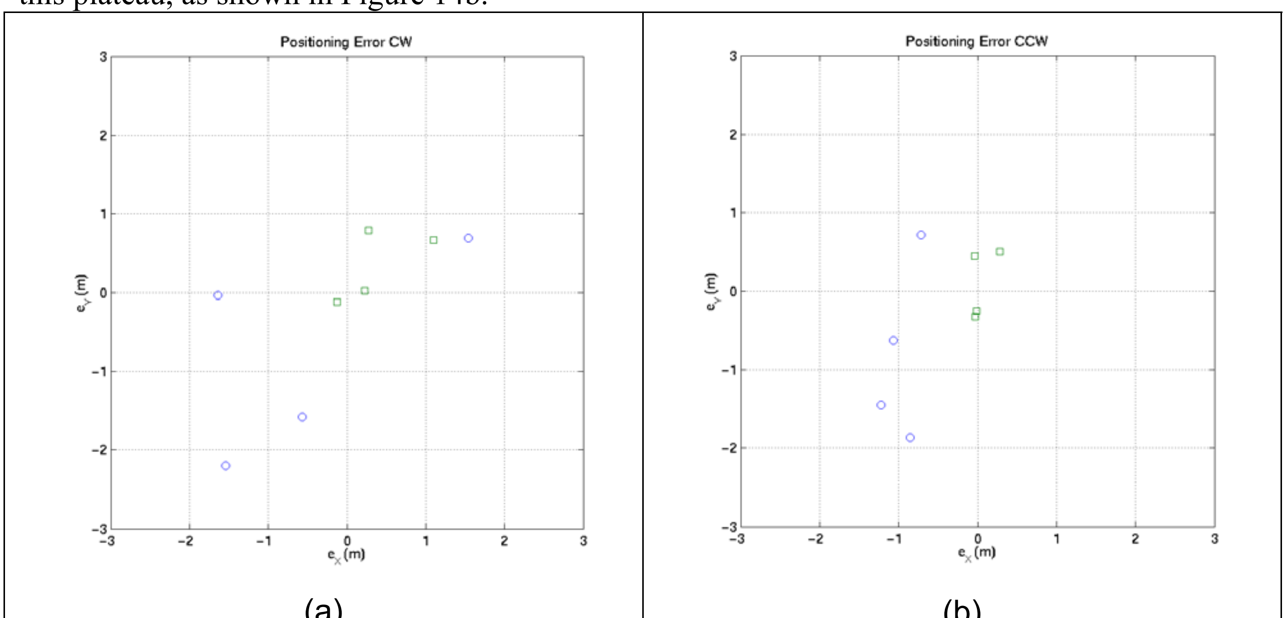
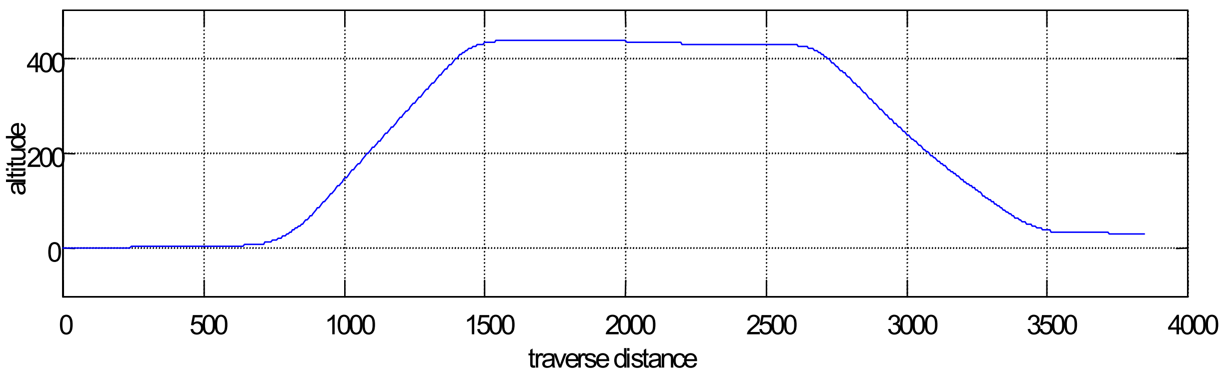


Figure 13: Final positioning errors of the robot. Blue circles show the errors when using the fiber-optic gyro only, while green squares show the errors when using the fiber optic gyro with our FLEXnav tilt information. (a) Clockwise, (b) counter-clockwise.

(a)



(b)

Figure 14: a) Robot traveling over an elevated plateau, b) Plot of the z-component of the robot's position while traversing the plateau.

7. CONCLUSIONS

On rugged terrain momentary tilt information must be taken into account for correcting heading measurements, regardless of the quality of the main heading sensor (a fiber optic gyro, in our case here). To do so we have proposed and implemented a fuzzy logic expert rules-based navigation system, called FLEXnav. The FLEXnav system compensates for the comparatively poor performance of the low-cost sensors that were used to measure tilt, thereby making them suitable for measuring tilt in a fast moving mobile robot. The tilt correction provided by our FLEXnav system results in a ten-fold improvement in heading estimation accuracy on moderately rugged terrain, as compared to a system that uses only a single gyroscope for measuring heading or compared to systems that use only one low cost sensor modality to measure tilt (i.e., low-cost Corriolis gyros or accelerometers).

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Companies

Analog Devices, Inc., Norwood, MA 02062, USA, http://www.analog.com.

Gyration, 12930 Saratoga Avenue, Bldg. C, Saratoga, CA 95070, USA, http://www.gyration.com.

KVH Industries, Inc., 8412 W. 185th St., Tinley Park, IL 60477, USA, http://www.kvh.com.