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Mobile Robot Vision Tracking System Using Dead Reckoning & Active Beacons

Muhammad Muneeb Shaikh*, Wonsang Hwang*, Jaehong Park*, Wook Bahn*, Changhun Lee*, Taeil Kim*, Kwang-soo Kim, and Dong-il "Dan"Cho***

** Department of Electrical Engineering and Computer Sciencet ASRI/ISRC, Seoul National University, Seoul, Korea, (Tel:+82-2-880-6488; e-mail: muneeb; wshwang; jaehong; wook03; chlee; ehoiz; dicho@snu.ac.kr).*
*** Department of Control and Instrumentation Engineering, Hanbat National University, Daejeon, Korea, (e-mail: kskim@hanbat.ac.kr).*

Abstract: This paper presents a new vision tracking system for mobile robot by integrating information received from encoders, inertial sensors, and active beacons. The proposed system accurately determines mobile robot position and orientation using relative and absolute position estimates, and rotates the camera towards the target during locomotion. Among the implemented sensors, the encoder data give relatively accurate robot motion information except when wheels slip. On the other hand inertial sensors have the problem of integration of noisy data, while active beacons are slow when compared to other sensors. The designed system compensates the sensors limitations and slip error by switching between two Kalman filters, built for slip and no-slip cases. Each Kalman filter uses different sensors combination and estimates robot motion respectively. The slip detector is used to detect the slip condition by comparing the data from the accelerometer and encoder to select the either Kalman filter as the output of the system. Based on the proposed sensor fusion method, a vision tracking system is implemented on a two-wheeled robot. The experimental results depict that proposed system is able to locate robot position with significantly reduced position errors and successful tracking of the target for various environments and robot motion scenarios.

Keywords: Mobile robots, sensor fusion, localization, Kalman filter, vision tracking system.

1. INTRODUCTION

Vision tracking technology is used in mobile robots to enhance their visual sensing ability and enable them to track the target continuously. Vision tracking systems using robot motion information have been researched for number of years, for instance, E. S. Shim *et al*. (2009), and A. Lenz *et al.* (2008). However, in vision tracking systems accurate localization of mobile robot for different robot motion scenarios and environmental conditions remains an essential task.

For accurate localization of mobile robot, various sensors and techniques have been employed and are characterized as: relative localization and absolute localization, J. Borenstein *et al.* (1997). Relative localization or dead reckoning technique uses kinematic model of the robot to compute the position of the robot relative to its start position. It determines the position and orientation using on-board sensors, such as encoders, gyroscopes, accelerometers etc. However, the conventional dead-reckoning method has the problem of accumulating wheel slippage error which limits its application. The absolute localization technique obtains the absolute position of robot using beacons, landmarks or satellite-based signals such as Global Positioning System (GPS). The position of the robot is externally determined and is independent from integration of noisy data or wheel slippage of mobile robot.

To improve the performance of localization systems sensor fusion technology is used. J. Borenstein *et al.* (1996) introduced a method called Gyrodometry, for combining data from gyroscope and encoders to accurately determine the position of the robot. W. Hwang *et al.* (2010) presented a method for sensor data fusion using two Kalman filters, and a slip detector to decide the selection of either Kalman filter model. However, during the slip conditions, their system relies on the conventional dead reckoning system, which leads their system to the problem of accumulating wheel slippage error.

In the proposed system, we employ active beacons along with the low cost inertial sensors for the slip case. The Extended Kalman filter is used to effectively combine the data and reduces the errors. As the data from the active beacons is independent of robot wheels slip, it enables the designed system to locate its accurate position even during slip condition. While Kalman filter designed for no-slip case utilizes the dead reckoning method of sensor fusion by combining the data from the encoders and gyroscope. The slip detector is used to detect the slip condition by comparing the data from the accelerometer and encoder to select the either Kalman filter as the output of the system. These position estimates are then used to rotate the camera to track the target continuously. The designed system is evaluated by performing experiments for various robot motion scenarios and environmental conditions, experimental results show

successful position estimation of the robot and vision tracking of the target.

This paper is organized as follows: Section 2 gives overview of sensor modeling for each sensor, while section 3 explains the sensor fusion algorithm in detail. The vision tracking principle is explained in section 4. Experimental setup and the experimental results are depicted in Section 5. Finally, we conclude this paper in section 6.

2. SENSOR MODELING

2.1 Odometry

Odometric estimation is based on the data from robot's encoder. The encoder is a sensor attached to a rotating object (such as a wheel or motor) to measure rotation. By measuring rotation we can determine displacement, velocity, acceleration, or the angle of a rotating sensor.

Robot's position and orientation can be determined by using the robot velocity and orientation obtained from the encoder data.

$$p_k = \begin{bmatrix} x_k \\ y_k \\ \theta_k \end{bmatrix} = \begin{bmatrix} x_{k-1} + v_{k-1}.\Delta t.\cos(\theta_{k-1}) \\ y_{k-1} + v_{k-1}.\Delta t.\sin(\theta_{k-1}) \\ \theta_{k-1} + w_{k-1}.\Delta t \end{bmatrix} \quad (1)$$

$$v = \frac{r_k + l_k}{2} \qquad w = \frac{r_k - l_k}{d} \quad (2)$$

where d is robot wheelbase, r_k and l_k is the distance transverse by robot's right and left wheel respectively.

Odometry is based on the assumption that wheel revolutions can be translated into linear displacement relative to the floor. This assumption is only true if there is no slippage in the robot's wheels. If there is a slip, then the associated encoder would register wheel revolutions even though these revolutions would not correspond to a linear displacement of the wheel.

2.2 Inertial Measurement Unit

The inertial measurement unit used for this system comprises of the low cost Microelectromechanical Systems (MEMS) based 3-axis accelerometer and z-axis gyroscope. In order to perform the signal processing of the inertial sensors a sensor module is developed which contains a microcontroller unit and a RS232 chip along with the sensors.

A gyroscope is used to measure the orientation of the robot. The angular velocity measured by the gyroscope can be integrated to give the orientation.

$$\theta_k = \theta_{k-1} + w \cdot \Delta t \quad (3)$$

where w is the angular velocity measured by the gyroscope.

Gyros have inherently large drift errors which can be modeled by an exponential curve and determined experimentally as done by Barshan and Durrant-Whyte (1995).

The accelerometer on the other hand measures the linear acceleration of the robot which can be integrated once to give the velocity and twice to attain the position of the robot. However, this integration causes the accumulation of error which limits the application of accelerometers to the case when the data from the other sensors are unreliable. The equations governing the calculation of position from the accelerometer data are given by:

$$\begin{aligned} v_{k+1} &= v_k + a_k \cdot \Delta t \\ x_{k+1} &= x_k + v_k \cdot \Delta t \end{aligned} \quad (4)$$

where a_k is the acceleration measured by the accelerometer.

2.2 Active Beacons

The absolute position and attitude of a vehicle in the laboratory environment can be sensed by using an indoor GPS system, Zimmerman *et al.* (1997). However, the system is too complex and expensive for robotic applications. Beacon systems on the other hand can provide an economical solution for the indoor environment, L. Kleeman (1989).

The active beacon system which we used for this application is composed of four transmitters, called beacons, two ultrasonic sensors and a tag. The beacons are mounted on the poles, and two ultrasonic sensors and a tag are mounted on the head of mobile robot. The active beacon system used for the experiment is shown in Fig.1.

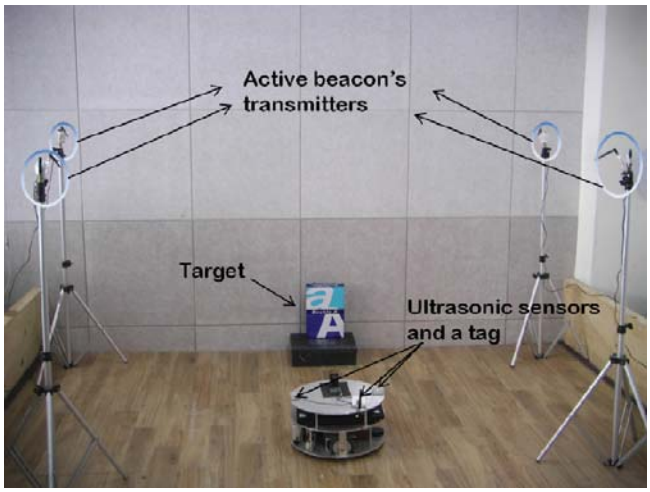

Fig.1. Active Beacon System used for determining absolute position of robot.

Active beacon system uses two ultrasonic sensors, which sends omni-directional ultrasonic signal, and a tag to transmit Radio Frequency (RF) signal to each beacon. Beacons after receiving the ultrasonic and RF signals determines the time of flight of ultrasonic signal and calculates the distance between beacon and mobile robot. Each beacon then sends calculated distance to the tag through RF signal. The x, y coordinates and orientation of robot is determined by employing

triangulation technique, J. C. Jin & I. O. Lee (2007). The specifications of active beacon system are given below in Table 1.

Table 1. Specifications of Active Beacon System

Size (mm)	Beacon	35 x 68 x 18	RF transmission	2.4~2.485 GHz
	Tag	90 x 58 x 17	Update Time	100 ms
	Sonar	35 x 35 x 15	Data Channel	128 channel
Voltage (DC V)	Beacon	3.3 ±5 %	Detection Range (m)	5 x 5 x 2.5
	Tag	5~15	Accuracy	±10 cm, ±2°

3. SENSOR FUSION ALGORITHM

As we have studied earlier, each sensor has certain limitations for different environmental conditions and robot motion scenarios, so they cannot depict the accurate position of robot alone. These limitations are overcome by effective combination of sensors data using two different Kalman filter models, designed for slip and no-slip cases. Each Kalman filter uses different sensors combination and estimates robot position respectively. Selection of either Kalman filter depends on the slip condition detected by the slip detector. Slip detector effectively decides the slip condition by comparing the velocities calculated by the encoder and accelerometer. The difference between the two velocities detects the slip condition, which is calculated using (5).

$$\sum_{k=n-l+1}^{n} \left| v_{encoder}(k) - v_{accel}(k) \right| > threshold \tag{5}$$

The threshold level is set after repeated experiments. The overall block diagram is shown in Fig.2.

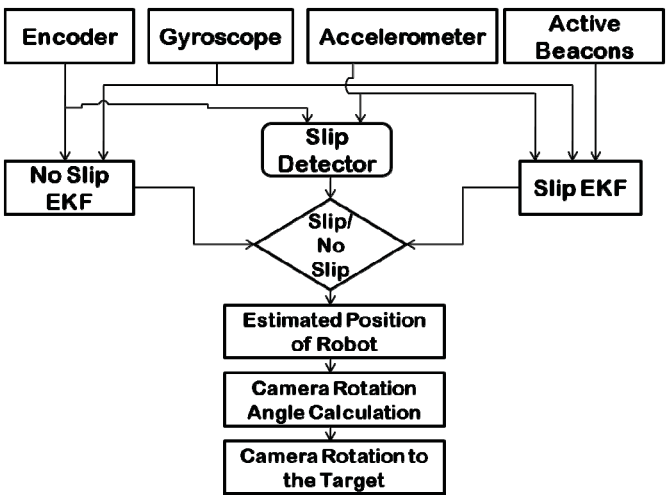

Fig. 2. Block diagram of the Vision Tracking System.

3.1 Kalman Filter for no-slip case

Kalman filter for no-slip case uses the Extended Kalman Filter (EKF) to fuse the data from the encoders and MEMS based gyroscope. In no-slip condition the combination of encoder and gyroscope gives relatively accurate results. The states of the Kalman filter are described in (6)

$$\underset{\sim}{x} = \begin{bmatrix} x & y & \theta_e & \theta_g \end{bmatrix}^T \tag{6}$$

where x, y are the position of the robot, and (θ_e, θ_g) are the attitude angle of the robot measured by encoder and gyroscope. The state model is shown in (7).

$$\underset{\sim}{\hat{x}}_{k+1} = \underset{\sim}{f}(\underset{\sim}{\hat{x}}_k, \underset{\sim}{w}_k) = \begin{bmatrix} \hat{x}_k + \cos\hat{\theta}_{e,k} \cdot \dfrac{r_k + l_k}{2} \\ \hat{y}_k + \sin\hat{\theta}_{e,k} \cdot \dfrac{r_k + l_k}{2} \\ \hat{\theta}_{e,k} + \omega_{e,k} \cdot \Delta t \\ \hat{\theta}_{g,k} + \omega_{g,k} \cdot \Delta t \end{bmatrix} + \underset{\sim}{w}_k \tag{7}$$

where $\underset{\sim}{f}$ is the system equation, $\hat{x}_k$, $\hat{y}_k$, $\hat{\theta}_{e,k}, \hat{\theta}_{g,k}$ are the estimates of the states at time k, r_k & l_k is the distance transverse by the robot's left & right wheel during the sampling time, $\omega_{e,k}$ & $\omega_{g,k}$ is the angular velocity measured at time k by the encoder and gyroscope, respectively, $\underset{\sim}{w}_k$ is the process noise added by the sensor noise, and Δt is the sampling time. Partial matrix for estimating error covariance and error covariance matrix is shown in (8) and (9) respectively.

$$F_k = \left. \frac{\partial \underset{\sim}{f}}{\partial \underset{\sim}{x}} \right|_{\underset{\sim}{x} = \underset{\sim}{\hat{x}}_k} = \begin{bmatrix} 1 & 0 & -\sin\hat{\theta}_k \cdot \dfrac{r_k + l_k}{2} & 0 \\ 0 & 1 & \cos\hat{\theta}_k \cdot \dfrac{r_k + l_k}{2} & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{8}$$

$$P_{k+1} = F_k P_k F_k^T + Q_k \tag{9}$$

where P_k is the error covariance matrix at time k, and Q_k is the covariance matrix of the noise $\underset{\sim}{w}_k$.

The measurement, in this case, consists of the measurement from encoder and gyroscope sensors. The measurement update equations are expressed in (10) and (11).

$$z_k = h(\underset{\sim}{\hat{x}}_k^-, v_k) = \hat{\theta}_{e,k}^- - \hat{\theta}_{g,k}^- + v_k \tag{10}$$

$$H_k = \frac{\partial h}{\partial \hat{\underset{\sim}{x}}_k^-} = \begin{bmatrix} 0 & 0 & 1 & -1 \end{bmatrix} \tag{11}$$

where h is the measurement equation, $\hat{x}_k^-$, $\hat{y}_k^-$, $\hat{\theta}_{e,k}^-$, $\hat{\theta}_{g,k}^-$ are the priori estimates of the states at time k, and v_k is the measurement noise.

$$\begin{aligned} K_k &= P_k^- H_k^T (H_k P_k^- H_k^T + M_k R_k M_k^T)^{-1} \\ \hat{\underset{\sim}{x}}_k^+ &= \hat{\underset{\sim}{x}}^- + K_k [z_k - h_k(\hat{\underset{\sim}{x}}_k^-, 0)] \\ P_k^+ &= (I - K_k H_k) P_k^- \end{aligned} \tag{12}$$

where K_k is the Kalman gain at time k, $\hat{\underset{\sim}{x}}_k^+$ is the posteriori estimate of the state at time k, R_k is the covariance of the measurement noise, I is the identity matrix, P_k^+ is the posteriori estimate of the error covariance of the state while P_k^- is the priori estimate.

3.2 Kalman Filter for slip case

During the slip conditions encoders cannot be utilized for position estimation as they give erroneous results. Subsequently, an accelerometer is used to calculate the velocity of robot by accumulating its acceleration, and gyroscope is used to determine the attitude of the robot. But, inertial sensors alone cannot provide the accurate results as they accumulate the errors arising from the bias and noise effects. To overcome this problem active beacons are used along with the inertial sensors. Inertial sensors provide the time update for the Kalman filter while active beacons update the measurement model to correct the errors. Extended Kalman filter is used to linearized the errors and estimate the states shown in (13).

$$\underset{\sim}{x} = \begin{bmatrix} x & y & \theta \end{bmatrix}^T \tag{13}$$

where x, y are the position of the robot, and θ is the attitude angle of the robot.

The state model is depicted in (14), while partial matrix for estimating error covariance and error covariance is calculated in (15) & (16).

$$\hat{\underset{\sim}{x}}_{k+1} = \underset{\sim}{f}(\hat{\underset{\sim}{x}}_k, \underset{\sim}{w}_k) = \begin{bmatrix} \hat{x}_k + \hat{v}_k \cdot \cos\hat{\theta}_k \cdot \Delta t \\ \hat{y}_k + \hat{v}_k \cdot \sin\hat{\theta}_k \cdot \Delta t \\ \hat{\theta}_k + \omega_k \cdot \Delta t \end{bmatrix} + \underset{\sim}{w}_k \tag{14}$$

where $\underset{\sim}{f}$ is the system equation, $\hat{x}_k$, $\hat{y}_k, \hat{\theta}_k$ are the estimates of the states at time k, v_k is the velocity calculated by accumulating the acceleration from the accelerometer at time k, ω_k is the angular velocity from the gyroscope at time k, $\underset{\sim}{w}_k$ is the process noise added by the sensor noise, and Δt is the sampling time.

$$F_k = \left.\frac{\partial \underset{\sim}{f}}{\partial \underset{\sim}{x}}\right|_{\underset{\sim}{x}=\hat{\underset{\sim}{x}}_k} = \begin{bmatrix} 1 & 0 & -\hat{v}_k \cdot \sin\hat{\theta}_k \cdot \Delta t \\ 0 & 1 & \hat{v}_k \cdot \cos\hat{\theta}_k \cdot \Delta t \\ 0 & 0 & 1 \end{bmatrix} \tag{15}$$

$$P_{k+1} = F_k P_k F_k^T + Q_k \tag{16}$$

Equations (17), (18) & (19) express the measurement update model as:

$$z_k = h(\hat{\underset{\sim}{x}}_k^-, v_k) = \begin{bmatrix} \hat{x}_k^- \\ \hat{y}_k^- \\ \hat{\theta}_k^- \end{bmatrix} + v_k \tag{17}$$

$$H_k = \frac{\partial h}{\partial \hat{\underset{\sim}{x}}_k^-} = \begin{bmatrix} 1 & 1 & 1 \end{bmatrix} \tag{18}$$

$$\begin{aligned} K_k &= P_k^- H_k^T (H_k P_k^- H_k^T + M_k R_k M_k^T)^{-1} \\ \hat{\underset{\sim}{x}}_k^+ &= \hat{\underset{\sim}{x}}^- + K_k [z_k - h_k(\hat{\underset{\sim}{x}}_k^-, 0)] \\ P_k^+ &= (I - K_k H_k) P_k^- \end{aligned} \tag{19}$$

where h is the measurement equation, $\hat{x}_k^-$, $\hat{y}_k^-$, $\hat{\theta}_k^-$ are the priori estimates of the states at time k, v_k is the measurement noise, K_k is the Kalman gain at time k, $\hat{\underset{\sim}{x}}_k^+$ is the posteriori estimate of the state at time k, R_k is the covariance of the measurement noise, I is the identity matrix, P_k^+ is the posteriori estimate of the error covariance of the state while P_k^- is the priori estimate.

4. VISION TRACKING PRINCIPLE

The proposed vision tracking system receives the robot's estimated position information from the either Kalman filter block. The mobile robot has in-plane linear motion along the x and y axis, and rotation motion along the z-axis. Fig. 3 shows the robot's motion and location information in the Cartesian coordinate system. The change in the angular position of the robot is expressed by $\Delta\theta$, and is calculated by using (20).

$$\Delta\theta = \tan^{-1}\left(\frac{X - x}{Y - y}\right) - \theta \tag{20}$$

Where X and Y are the position of the target, and x, y and θ are the position and orientation of the robot is estimated by the Kalman filter.

As robot attains the new position, $\Delta\theta$ is updated to indicate the change in the position of robot from its previous value. This updated angular information is then fed to the DC motor, which is used to rotate the camera towards the target. This vision tracking phenomena helps robot locating the target as it propagates. By using the (20) we can calculate the rotation angle of the camera and rotates the camera to track the target continuously.

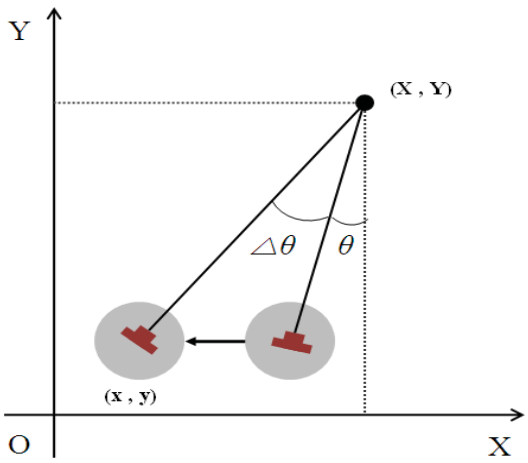

Fig.3. Cartesian Coordinate system depicting robot's motion and its location.

5. EXPERIMENTAL RESULTS

5.1 Experimental Setup

The experimental setup consists of a mobile robot with built-in wheel encoders. An IMU block consisting of a MEMS gyroscope and accelerometer is used to obtain inertial sensor measurement. Active beacons are used to provide the absolute position of robot. The experimental setup and robot motion environment is shown in Fig. 4.

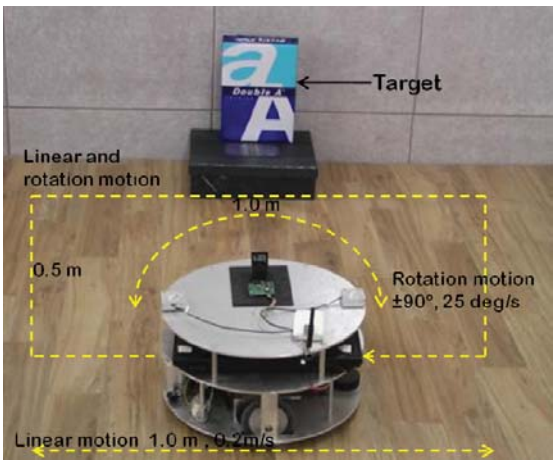

Fig.4. Experimental condition & scenarios for robot motion.

5.2 Experimental Results

To evaluate the performance of proposed system, various experiments are performed. These experiments include simple translational as well as translational and rotational motion combined. Each test is performed through pre-programmed path and the performance of Kalman filter's estimated results are compared with the results of other sensors and actual path transverse by the robot.

The first experiment tests simple translational motion where the robot moves 1 meter forward and then move 1 meter backward. The robot position information is continuously obtained from various sensors and the EKF system, result is shown in Fig. 5.

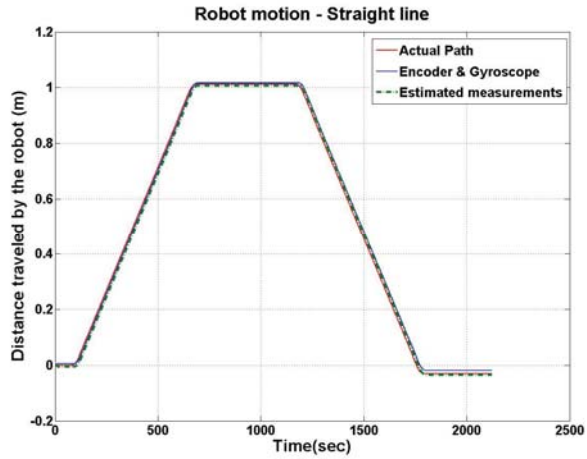

Fig. 5. Distance from the origin measured by various sensors during translational motion.

The next experiment is performed to evaluate the system performance during the translation and rotational motion, so robot transverse in rectangular shape path. The EKF estimates give more accurate results then the encoder and gyroscope values combined without Kalman filter, results are depicted in Fig.6.

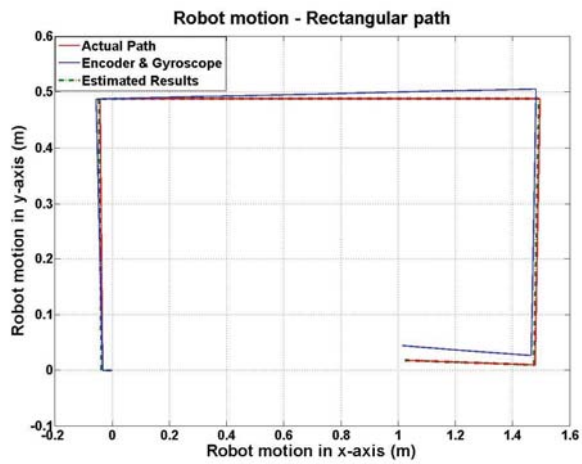

Fig.6. Robot motion in rectangular path measured by various sensors depicting translational and rotational motion.

The third experiment is performed for the slip condition. In this experiment robot has to travel 1 meter forward and 1

meter backward, but robot motion is hindered by placing a barrier in its path when it is travelling backward. The total distance travelled from the origin as obtained from different sensors and the EKF system is plotted. Fig. 7 shows the performance of the system as compared with other sensors. A steep error in the encoder data can be seen at the point where slip occurs.

The developed system is able to detect the robot position accuraetly in various enviornmental conditions and robot motion scenarios. These estimates are then used for calculating the rotation angle of camera to track the target. Experimental results show succesfull tracking of target for all the conditions. The final position errors for the sensors and Kalman filter estimates along with the vision tracking success rate of target are summarized in table2.

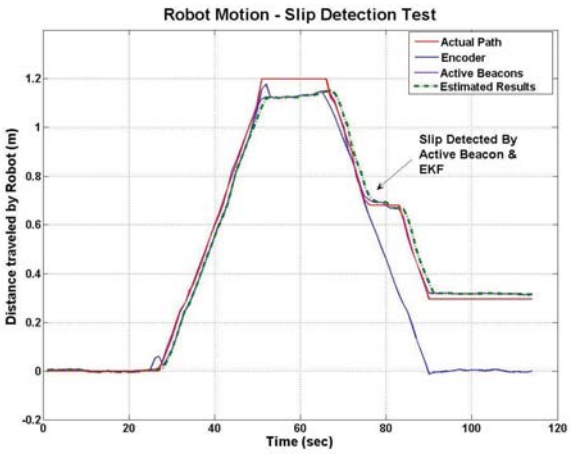

Fig.7. Distance from the origin measured by various sensors during slip experiments.

Table 2. Experimental Results for various robot motion and scenarios

Experiment	Sensors	Final position/Angle Errors	Vision Tracking Success Rate
Linear Motion	Encoder & Gyroscope	15 mm	98 %
	EKF	5 mm	
Rectangular Motion	Encoder & Gyroscope	x-axis: 95 mm, y-axis: 30 mm, heading: 1.89°	90 %
	EKF	x-axis: 16 mm, y-axis: 20 mm, heading: 1.02°	
Slip test	Encoder	296 mm	96 %
	EKF	25 mm	

6. CONCLUSION

This paper presents a vision tracking system by using dead reckoning and absolute localization technique. The designed system integrates the information received from the encoder, inertial sensors and active beacons. The proposed system efficiently overcomes the drawback of each sensor and robot motion by using two Kalman filter models and a slip detector. Experiments are performed for various robot motion scenarios in different conditions. Experimental results depict that proposed system is able to locate robot position and track the target under all the conditions. However, for tracking purposes results can be further improved if the vision sensor information is also considered.

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