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Data Fusion Using Ultra Wideband Time-of-Flight Positioning for Mobile Robot Applications

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***Abstract*—Self-localization of a robot is one of the most important requirements in mobile robotics. There are several approaches to providing localization data. The Ultra Wide Band Time of Flight provides position information but lacks the angle. Odometry data can be combined by using a data fusion algorithm. This paper addresses the application of data fusion algorithms based on odometry and Ultra Wide Band Time of Flight positioning using a Kalman filter that allows performing the data fusion task which outputs the position and orientation of the robot. The proposed solution, validated in a real developed platform can be applied in service and industrial robots.**

I. Introduction

A mobile industrial robot requires the ability to self-localize in an environment without human intervention. The task of estimating the pose of the robot on a map has been capturing the attention of researchers, developers, and technology transfer processes of mobile robots. These vehicles are commonly used to transport materials between workstations in warehouses and production lines. Localization systems in industrial environments, commonly use solutions that rely on artificial landmarks, such as the classic magnetic tape following, line tracking, or reflector-based laser triangulation [1], [3], [4].

One of the well-known localization systems is based on laser triangulation that requires several visible landmarks [1]. This method has the main disadvantage of requiring the installation of dedicated reflectors in the environment, which might be an impossible solution in some factories. Moreover, it is an expensive system, and landmarks should be added in the field of view of the robot laser scanner. Another localization method can use radio frequency. Instead of the Receive Signal Strength Indicator (RSSI) measurement, positioning is done with transit time methodology, Time of Flight (ToF). This method measures the running time of flight between a fixed tag module and receiver (Anchor). Ultra-wideband (UWB) modules from Decawave are used in this work. In this way, it allows a low-cost localization methodology and a $ready - to - go$ system. Unfortunately, this system only provides the position and not the orientation.

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On the other hand, odometry provides the orientation, but the cumulative localization error is a problem. The information provided by odometry and UWB technology is further processed through a data fusion filter. In this way, orientation can be achieved based on odometry. The Kalman filter (KF) combines both information and provides as output the position and orientation data [2].

This paper addresses the development of a mobile robot to validate the concept of data fusion from odometry and UWB ToF using a real application with its associated noise in measurements while keeping the safety of the robot.

The paper is organized as follows: section II presents the related work of localization considering the UWB technology. Then, section III addresses the system architecture where the odometry and UWB are described and the UWB model is stressed. Section IV presents the data fusion from odometry and UWB ToF data, whereas section V results are discussed. Finally, the last section rounds up the paper with conclusions and where some future work direction is pointed.

II. Background and Related works

Once mobile robot localization is a complex, challenging, and one of the most fundamental problems in robotics, several approaches exist in the community. Among the others, laser triangulation, matching algorithms, complex vision systems, odometry, and radio frequency are methodologies used to find the position of a robot [15].

In the matching algorithms, position estimation is commonly fused with dead reckoning data, using for that purpose probabilistic methods such as the KF family and the Particle Filters. There are matching algorithms that require prior knowledge of the navigation area. This prior knowledge can be an environment map, natural landmarks, or artificial beacons [5]. There are other types of matching algorithms that compute the overlapping zone between consecutive observations to obtain the vehicle displacement. One possible matching algorithm to estimate the quantity of angular and linear displacement of a vehicle between two different and consecutive configurations is the Iterative Closest Point (ICP) [7] [6].

Another common localization approach is to combine several solutions such as line following and laser triangulation [3], [4]. Meanwhile, in the last decade localization based on natural marks has been increasing [8]. These are composed of a set of distances and angles to the detected objects (such as doors, walls, furniture, ...) that can be acquired through an onboard laser range finder. This method has the main advantage of not requiring the installation of dedicated reflectors, which in some factories might not be a viable option. On the other hand, objects placed in different locations originate measuring errors.

An encoder is a kind of simple and important sensor and is mounted on most mobile robots with wheels. However, there are unavoidable accumulated errors for the dead reckoning (DR) based localization over long distances, in that it needs to utilize the previous position to estimate the next relative one and during which, the drift, the wheel slippage, the uneven floor and the uncertainty about the structure of the robot will together cause errors [15]. Odometry has been used for several years in mobile robots. Knowing the rotation of each wheel and its parameters (such as diameter, distance, and friction), it is possible to estimate the robot's pose in the environment. This is one of the first methodologies used to calculate the robot's position. A common and basic localization method called dead reckoning is used to estimate the position by counting wheel rotations with the help of encoders. Unfortunately, Dead reckoning is subject to cumulative errors, so it is common to combine different localization methods. Several works can be pointed out using odometry localization, such as image processing [13] or Wireless Sensor Networks [14].

Mobile robot localization with radiofrequency has been increasing its popularity. Ultra-wideband (UWB) is considered one of the most promising indoor positioning technologies currently available, especially due to its fine time resolution. Using ToF instead of signal power allows much more precision and robustness. UWB is a radio technology widely used for communications, that is recently receiving increasing attention for positioning applications. In these cases, the position of a mobile transceiver is determined from the distances to a set of fixed, well-localized beacons. Though this is a well-known problem in the scientific literature (the trilateration problem [1]), the peculiarities of UWB range measurements (basically, distance errors and multipath effects) demand a different treatment to other similar solutions, as for example, those based on a laser. There are authors that characterize the UWB ranges combined with particle filters within a variety of environments and situations [12] and apply UWB using spatial models [9]. UWB time of flight has already captured the researchers' attention that combines it with inertial sensors [11].

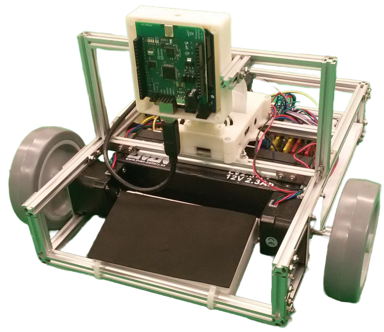

Fig. 1. Mobile robot prototype

The presented work uses a combination of odometry and UWB ToF to compute the position of a robot.

III. System architecture

A wheeled mobile robot prototype (28 cm x 35 cm) was developed having in mind the validation of the proposed positioning system, as shown in figure 1.

It is composed of two drive wheels and a castor wheel. Two stepper motors drive the differential mobile robot, a typical configuration in mobile robots. The maximum speed of the robot is 1 m/s. Meanwhile, the tests presented in the Results section were achieved with 10% of speed. It is powered by an onboard 12 V battery and a DC/DC step-down converter allows it to power the electronic modules composed by a Raspberry 3 model and an Arduino microcontroller. The upper level is composed of a Raspberry microcomputer that runs raspbian operating system and is responsible for KF processing, wi-fi communications, and decision. The Arduino microcontroller deals with the low-level control of motors, voltages, current, power management, and odometry.

Stepper motors are powered by Allegro MicroSystems - A4988 modules that handle the micro-stepping method and regulate the current limit.

A. Ultra Wideband Time of flight

Ultra-wideband (UWB) localization is a recent technology that promises to outperform many indoor localization methods currently available [10].

Time of flight describes methods that measure the time that an object, particle, electromagnetic or other wave takes to travel a distance. It is a technology used in in-depth cameras that allows measuring the distance of an object to the camera based on the travel time of the speed of light. Using radio frequency, there are some approaches that estimate the distance measuring the signal strengths (Receive Signal Strength Indicator, RSSI). Results are not much satisfactory because signal reflections and multi-path effects introduce errors and noise in measure. The distance between two Ultra Wideband (UWB) devices can be measured precisely by measuring the time that it takes for a radio wave to pass between the two

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TABLE I
AVERAGE AND CO-VARIANCE VALUES FOR POSITIONS (1,3), (2,2), (3,2), (3,4), (4,1) AND (5,4) IN MILLIMETERS

$\overline{x}$	$\overline{y}$	$e(x)$	$e(y)$	$Cov(x)$	$Cov(y)$	$Cov(x,y)$
1028.7	2906.0	28.7	-93.9	236.7	34.7	224.1
2033.8	1931.4	33.8	-68.5	640.8	688.1	1198.5
3046.7	1925.6	46.7	-74.3	497.9	-149.5	1311.5
2990.6	3907.5	-9.3	-92.4	343.3	32.1	318.4
4030.8	956.7	30.8	-43.2	111.6	82.2	431.2
5097.1	4018.1	97.1	18.1	359.5	-191.7	443.6

devices. It is a technology based on the IEEE 802.15.4-2011 standard, which can enable tagged objects to be located [16].

UWB is a radio technology that is characterized by its very large bandwidth compared with conventional narrowband systems and in particular features high positioning accuracy (due to a time resolution in the order of nanoseconds), and high material penetrability (due to a bandwidth typically larger than 0.5 GHz). UWB is considered one of the most promising indoor positioning technologies currently available, especially due to its fine time resolution [9].

UWB has been used for decades and is a well-established localization device [18] [9].

Decawave DW1000 is a single-chip, UWB-compliant, Wireless Transceiver based on Ultra Wideband techniques and provides a new approach to Real Time Location and Indoor Positioning Systems.

There are commercial products ready to use, based on the DW1000 Decawave chip that allows users to localize an anchor between tags like Pozyx [17].These modules provide the localization (x,y,z) but the orientation cannot be determined. One advantage of the proposed system makes use of a KF that estimates the orientation of the robot.

B. UWB - ToF localization Model

The model of the Ultra wide band can be achieved through several measurements in the field. It was acquired 256 samples of (x, y) measures for 6 positions, having the anchors placed in the bottom corners of a room of 6 x 5 meters. The average ($\overline{x}$ and $\overline{y}$), error in x and y ($e(x)$ and $e(y)$) and co-variance for x, y, and xy ($Cov(x)$, $Cov(y)$ and $Cov(x, y)$) for positions (1,3), (2,2), (3,2), (3,4), (4,1) and (5,4) in millimeters are presented in table I.

As a graphical view, Figure 2, presents the measures for different locations and respective error ellipses whereas Figures 3 and 4 present detailed information for two positions (1,3) and (2,3).

With the acquired information from these measurements, it is possible to compute the covariance matrixes useful to the KF design, as stressed in the next subsection.

C. Odometry

Odometry is a technique that uses the data from encoders to estimate the change in position. This method is sensitive to errors due to the integration of velocity measurements over time to give position estimates. In order to use odometry effectively it is required to combine other localization methods.

Dead reckoning is a method used to estimate the position by counting wheel rotations with the help of encoders. But there are unavoidable accumulated errors for DR-based localization over long distances, in that it needs to utilize the previous position to estimate the next relative one and during which, the drift, the wheel slippage, the uneven floor and the uncertainty about the structure of the robot will together cause errors [15]. Landmarks are commonly used to assist the dead reckoning

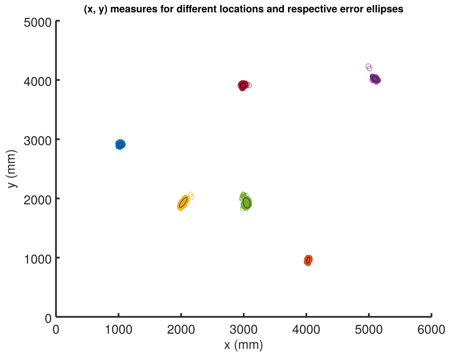

Fig. 2. (x,y) measures for different locations and respective error ellipses

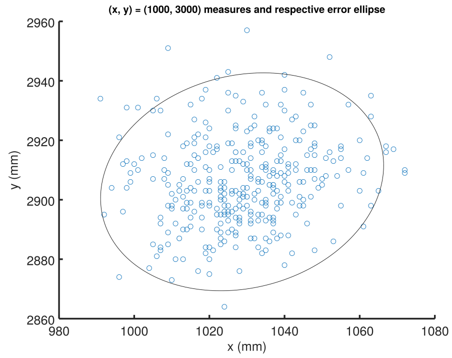

Fig. 3. (x,y) = (1000,3000) measures and respective error ellipses

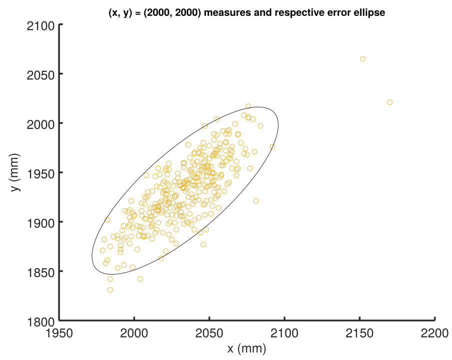

Fig. 4. (x,y) = (2000,2000) measures and respective error ellipses

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method in precise localization and to clear the accumulated errors of odometry [14].

IV. Localization data fusion

The KF implements the sensor fusion task. It receives x_p and y_p (position) from the ultra-wide band time of the flight module (UWB-ToF) and ω_L and ω_R (left and right wheel speeds) from the odometry system. It outputs the X_k state (equation 1) composed by x, y, and θ as the robot position and orientation as presented in Figure 5. In this case, the height of all tags and anchors was the same.

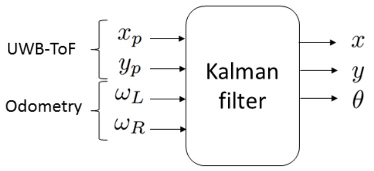

Fig. 5. KF inputs/outputs. Inputs: data from the UWB-ToF module and data from odometry (encoders). Output: Robot localization.

As a first filtering approach, it is necessary to remove the wrong measures from the UWB-ToF module. A median filter is applied to the x and y values eliminating unlikely measures and the filtered values are one input for the KF.

$$X_k = \begin{bmatrix} x \\ y \\ \theta \end{bmatrix} \tag{1}$$

$$\dot{X} = f(X, u) \tag{2}$$

where

$$u = \begin{bmatrix} v \\ \omega \end{bmatrix} \tag{3}$$

The observation estimate, Z:

$$Z = h(X) \tag{4}$$

From odometry (Figure 6), $v_L = \omega_L.r$ and $v_R = \omega_R.r$ where r is the wheel radius.

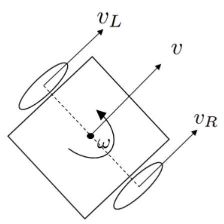

Fig. 6. Robot vectors.

The linear velocity (v) and angular velocity (ω) can be calculated as presented in equation 5 where d is the distance between wheels that equals 0.29 m.

$$v = \frac{v_L + v_R}{2} \quad \omega = \frac{v_R - v_L}{d} \tag{5}$$

Equation 2 ($\dot{X}$) can now be calculated as:

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} v.cos(\theta) \\ v.sin(\theta) \\ \omega \end{bmatrix} \tag{6}$$

F_k is the state transition model which is applied to the previous state X_{k-1}, expressed in Equation 7.

$$F_k = \begin{bmatrix} 1 & 0 & -\Delta t.v.sin(\theta) \\ 0 & 1 & \Delta t.v.cos(\theta) \\ 0 & 0 & 1 \end{bmatrix} \tag{7}$$

The Jacobian of h function is:

$$H_k = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \tag{8}$$

The measurement from UWB-ToF is Z_k:

$$Z_k = \begin{bmatrix} x_p \\ y_p \end{bmatrix} \tag{9}$$

1) Predict: This subsection addresses the prediction of state.
The predicted covariance estimate, P_k^- (until k instant).

$$P_k^- = F_{k-1} P_{k-1} F_{k-1}' + Q_{k-1} \tag{10}$$

where F_k is the state transition the model which is applied to the previous state x_{k1} and Q_{k-1} is the process noise covariance. The Q_{k-1} matrix can be written as equation 11.

$$Q_{k-1} = \begin{bmatrix} cov(v_x, v_x) & cov(v_x, v_y) & cov(v_x, \omega) \\ cov(v_x, v_y) & cov(v_y, v_y) & cov(v_y, \omega) \\ cov(v_x, \omega) & cov(v_y, \omega) & cov(\omega, \omega) \end{bmatrix} \tag{11}$$

Instead of working with v_x and v_y, it is possible to perform a rotation Rot (equation 12) to work with v and v_n (where v is the linear velocity whereas v_n is the normal velocity) we can assume $v_n = 0$ and $cov(v_n, v_n) = 0$ for robots turning on the spot.

$$\begin{bmatrix} v_x \\ v_y \\ \omega \end{bmatrix} = \begin{bmatrix} cos(\theta) & -sin(\theta) & 0 \\ sin(\theta) & cos(\theta) & 0 \\ 0 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} v \\ v_n \\ \omega \end{bmatrix} \tag{12}$$

Working with v and v_n, $Q_{k-1} = Rot \cdot Q_{k-1}' \cdot Rot^T$, where Q_{k-1}' is presented in equation 13, it is possible to reach the ratio between $cov(v, v)$ and $cov(\omega, \omega)$ presented in equation 16, assuming that v_L and v_R errors follow a normal distribution (N) centered in zero with a standard deviation of σ. Equations 14 and 15 present the distribution of v and ω.

$$Q_{k-1}' = \begin{bmatrix} cov(v, v) & 0 & 0 \\ 0 & cov(v_n, v_n) & 0 \\ 0 & 0 & cov(\omega, \omega) \end{bmatrix} \tag{13}$$

$$v \rightarrow 2 \cdot \frac{1}{4} \cdot N(0, \sigma^2) \tag{14}$$

$$\omega \rightarrow 2 \cdot \frac{1}{d^2} \cdot N(0, \sigma^2) \tag{15}$$

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$$cov(v, v) = \frac{4}{d^2} cov(\omega, \omega) \tag{16}$$

This methodology allows tuning the KF by one constant that can be found by performing a few experiences.

The prediction state estimate, X_k^- (until k instant)

$$X_k^- = f^*(X_{k-1}, u_{k-1}) \tag{17}$$

2) Update: This subsection addresses the Update process.

The measurement residual:

$$\tilde{Y_k} = Z_k - Z \tag{18}$$

The innovation covariance:

$$S_k = H_k P_k^- H_k' + R_k \tag{19}$$

where R_k is the observation noise covariance, which can be calculated based on the covariance average of measures points from the previous subsection as presented in Equation 20.

$$R_k = \begin{bmatrix} 3.654e^{-4} & 8.266e^{-5} \\ 8.266e^{-5} & 6.546e^{-4} \end{bmatrix} \tag{20}$$

The Kalman gain, K_k:

$$K_k = P_k^- H_k' S_k^{-1} \tag{21}$$

The updated state estimate, X_k:

$$X_k = X_k^- + K_k \tilde{Y_k} \tag{22}$$

The updated covariance estimate, P_k can be described:

$$P_k = (I - K_k H_k) P_k^- \tag{23}$$

V. Results

The localization system under validation was tested in the developed robot on a field of 6m x 5m (x,y). Three different paths (run #0, run #1, and run #2) were implemented and the error of the final position was measured. The odometry estimation is shown with blue lines whereas the KF prediction is shown with a green line. The magenta line shows the Pozyx measure and the light green shows the KF direction. The light blue shows the odometry angle direction and the green ellipse presents the covariance of the KF. All tests started at the position (x=2.2, y=1.2). The first path (run #0), presented in the screenshot of figure 7, is composed of some rotations, circles, and lines.

The second path (run #1) presented in the screenshot of figure 8 is composed of a rectangle (four 90 degrees counter-clockwise turns) and four lines.

As the last test (run #2) presented in figure 9, a kidnapping problem was addressed. The robot starts at the original position, follows in the xx axis, and in the position (3.2, 1,2) is moved (without moving wheels) to position (3.2, 1.9). It is obvious that the odometry data still remains in the same position, but the UWB ToF and the KF will perform the localization correctly.

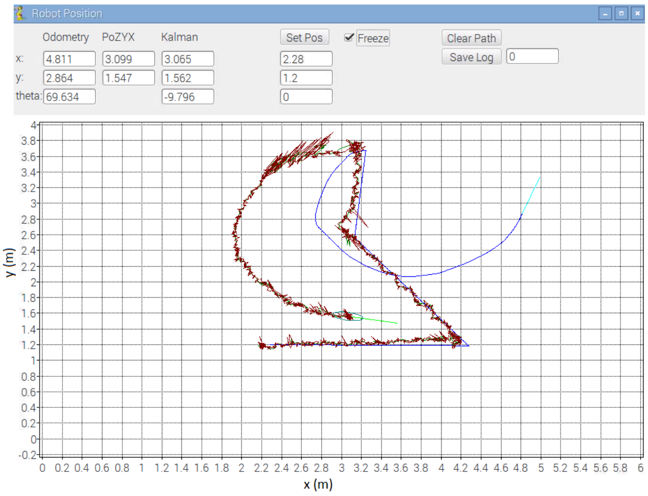

Fig. 7. XY map for run #0

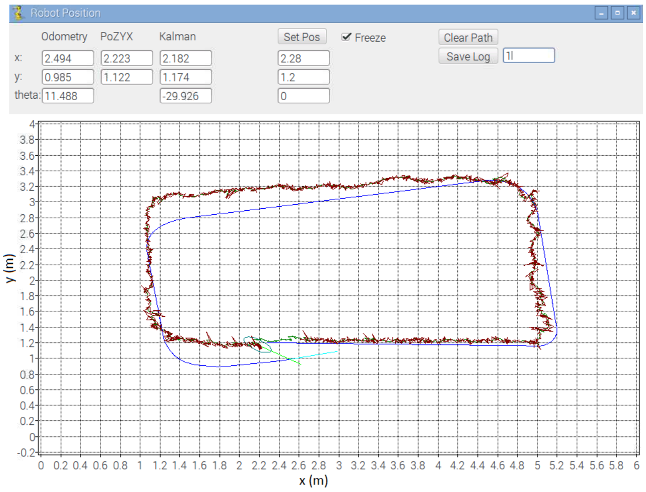

Fig. 8. XY map for run #1

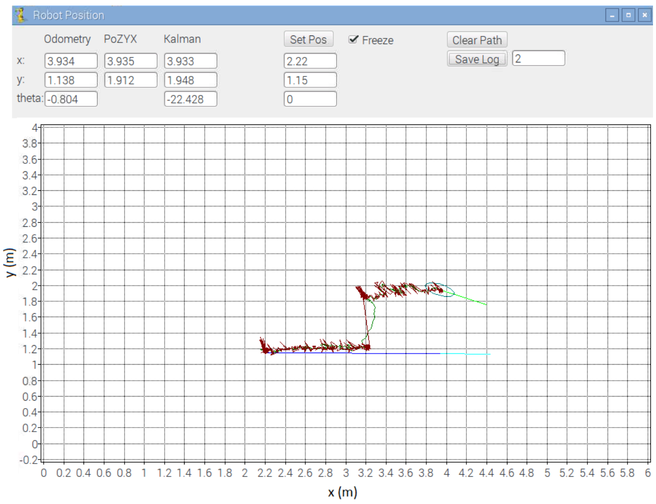

Fig. 9. XY map for run #2

TABLE II
MEAN ABSOLUTE ERROR FOR ODOMETRY, POZYX AND KALMAN (IN METERS AND DEGREES)

Mean absolute error							
Odometry			Pozyx		Kalman		
x	y	Theta	x	y	x	y	Theta
0.67	0.8	27.9	0.05	0.04	0.05	0.02	20.7

TABLE III
EUCLIDEAN MEAN ABSOLUTE ERROR FOR ODOMETRY, POZYX AND KALMAN (IN METERS)

Euclidean Mean absolute error		
Odometry	Pozyx	Kalman
1.02	0.065	0.059

In summary, it is possible to stress that the KF allows for the reduction of the error of the localization. In order to measure it, table II presents the error in x, y, and θ (meters and degrees).

Finally, the Euclidean distance means the absolute error is presented in Table III.

It is possible to conclude that, as expected, the odometry accumulates error and after just a few turns, the position error will increase. On the other hand, the UWB ToF is a localization system that computes the (x,y,z) position but lacks the angle of the robot. A KF can be used to perform the sensor fusion and the model of the KF can calculate the angle (θ) of the robot. Numerically, the odometry only provides an error of 1m (according to the test paths). The Pozyx module achieves a Euclidean error of about 6,5 cm. Combining odometry, with PoXYZ system and the model of the robot, it is possible to get the error of the system as 5,9 cm and the angle for orientation of 20.7 degrees.

VI. CONCLUSION AND FUTURE WORK

In this paper, it is used odometry and an ultra-wideband time-of-flight (UWB ToF) system to perform localization. The odometry, based on the wheels' angular speed, provides the angle and the position of the robot itself. A drawback of this approach is the cumulative error behavior of odometry. On the other hand, the UWB ToF modules compute the position of a tag based on the ToF distances between fixed anchors but this method doesn't provide the angular information. The proposed methodology used a KF to perform the data fusion between odometry and UWB ToF. The measured UWB ToF error model permits to design of an accurate KF that combines the position information for both systems and outputs the position and orientation of the mobile robot. The model of the robot implemented in the KF allows keeping the robot angle with a low error. This is one advantage of the proposed system that estimates the orientation of the robot that UWb ToF misses. The algorithms were implemented in a developed robot prototype that allows to validation of the proposed approach. The proposed methodology can be used in industrial and service robots without any installation of visible landmarks in the environment and also it is a low-cost solution compared with expensive laser-based localization systems. In future work, KF can make the data fusion from other sensors such as accelerometer/gyroscope and visual localization. A model of measured distances between tags an anchors can be acquired and triangulation accuracy could be improved.

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