ResearchGate

See discussions, stats, and author profiles for this publication at: https://www.researchgate.net/publication/303808254

Stochastic Wheel-Slip Compensation Based Robot Localization and Mapping

Article *in* Advances in Electrical and Computer Engineering · May 2016

DOI: 10.4316/AECE.2016.02004

CITATIONS
5

READS
387

4 authors, including:

Rakesh Kumar Sidharthan
HCL Technologies Pvt Ltd
35 PUBLICATIONS **115** CITATIONS
SEE PROFILE

Seshadhri Srinivasan
ABB
149 PUBLICATIONS **850** CITATIONS
SEE PROFILE

Valentina Emilia Balas
Aurel Vlaicu University of Arad
471 PUBLICATIONS **3,125** CITATIONS
SEE PROFILE

Some of the authors of this publication are also working on these related projects:

Project EC4 Project : Make the planet great again, really, no bla-bla View project

Project BioCell-NanoART = Novel Bio-inspired Cellular Nano-Architectures -- For Digital Integrated Circuits View project

All content following this page was uploaded by Valentina Emilia Balas on 12 June 2016.

The user has requested enhancement of the downloaded file.

[Downloaded from www.aece.ro on Sunday, June 12, 2016 at 10:15:23 (UTC) by 79.113.249.254. Redistribution subject to AECE license or copyright.]

Stochastic Wheel-Slip Compensation Based Robot Localization and Mapping

Rakesh Kumar SIDHARTHAN[1], Ramkumar KANNAN[2], Seshadhri SRINIVASAN[3], Valentina Emilia BALAS[4]

[1,2] *Electric Vehicle Engineering and Robotics (EVER) Lab, School of Electrical and Electronics Engineering, SASTRA Univeristy, Thanjavur 613401, Tamil Nadu, India*

[3]*Department of Engineering, University of Sannio, Benevento, Italy-82100*

[4] *Department of Automatics and Applied Informatics, Aurel Vlaicu University of Arad, Romania*

srakesh@eie.sastra.edu

***Abstract*—Wheel slip compensation is vital for building accurate and reliable dead reckoning based robot localization and mapping algorithms. This investigation presents stochastic slip compensation scheme for robot localization and mapping. Main idea of the slip compensation technique is to use wheel-slip data obtained from experiments to model the variations in slip velocity as Gaussian distributions. This leads to a family of models that are switched depending on the input command. To obtain the wheel-slip measurements, experiments are conducted on a wheeled mobile robot and the measurements thus obtained are used to build the Gaussian models. Then the localization and mapping algorithm is tested on an experimental terrain and a new metric called the map spread factor is used to evaluate the ability of the slip compensation technique. Our results clearly indicate that the proposed methodology improves the accuracy by 72.55% for rotation and 66.67% for translation motion as against an uncompensated mapping system. The proposed compensation technique eliminates the need for extro receptive sensors for slip compensation, complex feature extraction and association algorithms. As a result, we obtain a simple slip compensation scheme for localization and mapping.**

***Index Terms*—error compensation, Gaussian processes, mobile robots, motion estimation, simultaneous localization and mapping**

I. INTRODUCTION

Robot localization and mapping has wide-spread applications in exploring hazardous and difficult environments, docking, material handling, transportation, planetary explorations, robotic surgeries, autonomous navigation (see, [1-6]). The localization approaches in literature can be broadly classified [7] into three categories: *(1)* model based [8, 9], *(2)* extro-receptive sensors [10-15], and *(3)* dead reckoning [16]. Model based approaches use dynamic model of the robot to design a localization algorithm. Although, building robot models are simple, modeling their interactions with environment is rather difficult due to the uncertainties. Therefore, model based approaches are best suited for static environments. The need to have additional sensors such as global positioning system (GPS) [1,10], LIDAR [11-12], motion camera [13], ultrasonic sensor [14], received signal strength (RSS) sensor [15] and complexity associated with the feature extraction algorithms limit the use of extro-receptive sensor based localization methods.

Dead reckoning (DR) based localization[16] overcomes the shortcomings of the model based and extra receptive sensors approaches as it uses simple odometers and initial position to perform localization leading to reduced cost and complexity. In spite of such pressing advantages, performance and accuracy of the DR localization method is restricted by the wheel-slip forces. In particular, this is important for robots deployed in outdoor environments such as defense applications. Consequently, building reliable DR based localization algorithm requires good slip compensation [17] schemes. Our objective in this investigation is to build a slip compensation scheme that uses on-board robot sensors and wheel-slip model.

To reach the objectives, this investigation uses the measurements from robot internal sensor to model the wheel slip variations as linear Gaussian models. The slip is compensated by switching among these models based on the robot input i.e. duty ratio. As a result of the switching, a compensating velocity is generated that reduces the influences of the wheel-slip. Thus the proposed compensation scheme eliminates the need for costly sensors, feature extraction algorithms and complexities associated with existing wheel-slip compensation techniques.

In literature, significant attention has been devoted to slip compensation schemes for robot localization and mapping, and several methods are available. Existing techniques include fusion of extro-receptive and dead reckoning techniques [10-12, 14] by using stochastic filters such as Kalman filter [18], Extended Kalman filter [19] and Particle filters [12] for sensor fusion. The use of uncompensated odometers and the computation complexity with online feature extraction algorithms restricts the use of these compensation schemes. To overcome these issues, interactive multiple model (IMM) framework [9-10, 17, 20] for slip compensation has been proposed. Typically, in IMM methods, the robot models are designed for slip and no slip conditions either using conventional mathematical or fuzzy logic [20] techniques. To switch over these models, a switching mechanism using techniques like support vector machine [17] are employed. However, the wheel-slip differs from one robot to another, and depends on various factors such as terrain interaction, wheel force, acceleration and others. Capturing the influences of these factors with fuzzy or mathematical approach is rather difficult. Furthermore, these approaches cannot use experimental data inherently in their design. On the other hand, experimental data provides

Digital Object Identifier 10.4316/AECE.2016.02004

1582-7445 © 2016 AECE

[Downloaded from www.aece.ro on Sunday, June 12, 2016 at 10:15:23 (UTC) by 79.113.249.254. Redistribution subject to AECE license or copyright.]

valuable information to model slip. Therefore, models that use measurement data to capture uncertainty in wheel-slip compensation technique are required.

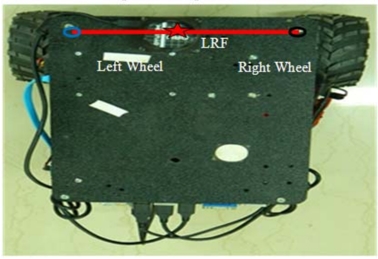

Figure 1. Wheeled mobile robot with LRF

This investigation proposes a modified IMM based approach to design slip compensation mechanism for dead-reckoning based robot localization and mapping. Main contributions of this investigation are: *(i)* IMM based stochastic slip compensation technique for dead-reckoning based localization that uses linear Gaussian models to capture the uncertainties in wheel slip, *(ii)* localization and mapping algorithm that builds on the compensation technique, *(iii)* propose a new validation metric called the map spread factor (MSF) for benchmarking the slip compensation scheme, and *(iv)* experimental validation of the proposed slip compensation based localization and mapping algorithm. Our experiments demonstrate that the proposed slip compensation scheme improves the mapping by 72.55% for rotation motion and 66.67% for translation motion as compared to uncompensated system.

Rest of the paper is organized as follows; Section II presents the hardware specification, classification of robot motion, and the robot dynamic model. Section III, presents the experiment performed to quantify wheel-slip for a given test condition and the role of linear Gaussian models are also described. Section IV, presents the formulation of MSF and its background in validating the mapping performance. The experimental results and evaluate the performance of localization and mapping algorithms are presented in Section V. Conclusions and future directions of the investigation are presented in Section VI.

II. SINGLE WHEEL TURN MOBILE ROBOT

To design the slip compensation scheme, Coroware®-CoroBot classic two wheel drive (CL2) mobile robot (Fig. 1) is used as the reference model. It is a differential drive robot with two rear and one caster wheel in the front. The speed and direction of the robot is changed by varying the duty ratio of the pulse-width modulation based voltage controller. A high speed optical shaft encoder measures the wheel displacement as quantized distances called ticks ($d_{tic} \in \mathrm{Z}$). The velocity of the robot wheels can be calculated using rate of change of the tick values and a tick conversion factor (T_{cf}) which converts the ticks to corresponding centimeters.

$$V_{lw}(n) = T_{cf}\frac{\Delta ld_{tic}}{\Delta t} \tag{1}$$

$$V_{rw}(n) = T_{cf}\frac{\Delta rd_{tic}}{\Delta t} \tag{2}$$

where, $V_{lw}(n)$ and $V_{rw}(n)$ are the instantaneous right and left wheel velocity in cm/s respectively and Δld_{tic} and Δrd_{tic} are the difference in measured tick displacement. The tick conversion factor can be calculated as ($T_{cf} = 2\pi r_w / R_{tic}$) using the robot wheel radius (r_w) in cm and (R_{tic}) ticks taken for one revolution of the robot wheel.

In order to design the slip compensation scheme, the robot is operated in single wheel turn mode; a special form of differential drive mode in a two wheel drive mobile robots that has been used to estimate the turning efficiency and quantify the amount of wheel slip in angular motion [21]. Typically, the effect of wheel slip will be predominant during acceleration/deceleration [22] and in angular motion that requires a slip compensation model. This is due to the robot experience a continuously change in torque direction during the robot motion. This investigation develops slip compensation model for accelerated angular motion, with the robot cross-section length (L) as radius and the stationary wheel as the center whose measured velocity (V_{rm}) is given by (3).

$$V_{rm}(n) = \begin{Bmatrix} V_{rw}(n) \\ V_{lw}(n) \end{Bmatrix} \Big| \begin{Bmatrix} V_{lw}(n) = 0 \\ V_{rw}(n) = 0 \end{Bmatrix} \tag{3}$$

With the choice of control inputs, the robot can be operated in four different rotation and two translation modes depending with different duty ratios (D_{lw} for left wheel and D_{rw} for right wheel) applied to the left and right wheel, respectively, as shown in Table I.

TABLE I. TYPES OF ROBOT MOTION

Motion Type	Control Signal	Center of Rotation	Direction of Rotation
Left wheel forward (LF)	$D_{lw} > 0$ $D_{rw} = 0$	Right Wheel	Clockwise
Left wheel reverse (LR)	$D_{lw} < 0$ $D_{rw} = 0$	Right Wheel	Anti-clockwise
Right wheel forward (RF)	$D_{lw} = 0$ $D_{rw} > 0$	Left Wheel	Clockwise
Right wheel reverse (RR)	$D_{lw} = 0$ $D_{rw} < 0$	Left Wheel	Anti-clockwise
Robot Forward	$D_{lw} > 0$ $D_{rw} > 0$	---	---
Robot Reverse	$D_{lw} < 0$ $D_{rw} < 0$	---	---

For localization and mapping algorithm, the mathematical model of the robot is derived as follows. The Euclidean distance between the center of the robot to its wheels (r_{lw_rc} and r_{rc_rw} for left and right wheels) is given by,

$$r_{lw\_rc} = r_{rc\_rw} = \frac{L}{2} \tag{4}$$

The relative position of the wheels for a givens robot center (x_{rc}, y_{rc}) and robot barring (θ_{bar}) in global coordinates can be calculated as follows, from (4), the position of the robot left wheel (x_{lw}, y_{lw}) and right wheel (x_{rw}, y_{rw}) can be given by (5) and (6),

[Downloaded from www.aece.ro on Sunday, June 12, 2016 at 10:15:23 (UTC) by 79.113.249.254. Redistribution subject to AECE license or copyright.]

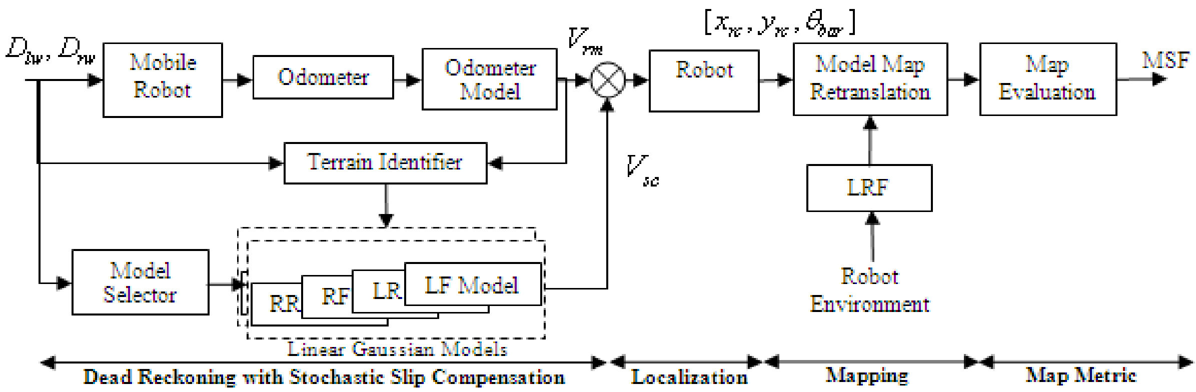

Figure 2. Robot localization and mapping system with proposed slip compensation technique

$$\begin{bmatrix} x_{lw} \\ y_{lw} \end{bmatrix} = \mathbf{A} + \begin{bmatrix} x_{rc} \\ y_{rc} \end{bmatrix} \tag{5}$$

$$\begin{bmatrix} x_{rw} \\ y_{rw} \end{bmatrix} = -\mathbf{A} + \begin{bmatrix} x_{rc} \\ y_{rc} \end{bmatrix} \tag{6}$$

where,

$$\mathbf{A} = [\frac{L}{2}\cos\theta_{bar}, \frac{L}{2}\sin\theta_{bar}]^t$$

The center of the robot and its bearing are calculated using the instantaneous wheel velocities and the center of rotation (x_{CR}, y_{CR}). Based on the wheel velocities the center of rotation will change as shown in (7). Thus the overall robot model can be derived as in (8).

$$\begin{bmatrix} x_{CR}(n) \\ y_{CR}(n) \end{bmatrix} = \left\{ \begin{bmatrix} x_{lw}(n-1) \\ y_{lw}(n-1) \end{bmatrix} \middle| \, |V_{rw}(n) > 0| \atop \begin{bmatrix} x_{rw}(n-1) \\ y_{rw}(n-1) \end{bmatrix} \middle| \, |V_{lw}(n) > 0| \right\} \tag{7}$$

$$\begin{bmatrix} x_{rc}(n) \\ y_{rc}(n) \\ \theta_{bar}(n) \end{bmatrix} = \begin{bmatrix} \frac{L}{2}\cos\theta_{bar}(n-1) \\ \frac{L}{2}\sin\theta_{bar}(n-1) \\ \frac{1}{L}(V_{lw}(n)+V_{rw}(n)) \end{bmatrix} + \begin{bmatrix} x_{CR}(n) \\ y_{CR}(n) \\ \theta_{bar}(n-1) \end{bmatrix} \tag{8}$$

In this mode the robot will always be in angular motion which can be used to evaluate the turning efficiency of the wheels in robot itself rather than having a separate test set up as in [22].

III. Proposed Localization And Mapping Methodology

The proposed slip compensation approach in this investigation uses simple sensors and dead-reckoning based approach for robot localization and mapping. To this extent, odometers fitted to each wheel of the mobile robot were used as dead reckoning sensor, whose incremental measurements are used to determine the robot navigation path and for building global map from local maps. The measurements thus obtained are subjected to error due to slip forces arising from wheel-terrain interaction, which in-turn depends on the wheel speed, type of wheel motion, and terrain type. In order to compensate these slip forces, this investigation proposes a stochastic slip compensation technique that uses Gaussian distribution to model wheel-slip. The compensation schemes uses experiments to obtain the Gaussian models that are used to generate slip compensation velocity that works against the measured velocity in run-time. This Gaussian description of wheel-slip results in a hybrid model wherein the compensation model is selected depending on the type of motion described in Table I and based on the terrain type.

With the compensated robot velocity, the robot can be localized using the robot model described by (8). This instantaneous robot location is used for mapping the robot environment using the local map scans. To acquire the local map scans, a laser range finder (LRF) was fitted on top of the mobile robot (Fig. 1) which scans the obstacles in the environment to produce a scan of local area in its vicinity. The acquired local scans will be translated to its original global position using the localized robot position and accumulated to reconstruct the original map of the environment.

Finally the quality of the reconstructed map was evaluated using MSF which in turn reflects the accuracy of localization and its slip compensation efficiency. This creates a framework in which the slip compensation technique can be evaluated in a more reliable and realistic procedure as shown in Fig. 2.

A. *Quantification of wheel slip*

Wheel slip causes perturbations in robot velocity measurements leading to performance degradation of dead reckoning based localization methods. Among the factors causing perturbation in measurements, terrain type is a predominant one. A hard surfaced terrain like cement concrete will increase the slip force leading to increase in measured robot wheel velocity where as a soft or slippery surface will lead to reduction in measured robot wheel velocity.

The perturbations in measurements can be detected by knowing the actual velocity of the robot accurately, which in-turn requires reliable measurement technique. To obtain such measurement, this investigation uses a binary measurement technique using distance measurement unit (DMS) with simple form of feature extraction and data association makes it to be accurate and reliable. The DMS which is an infrared (IR) based reflection type sensor was fitted focusing outwards along the vertical axis of each wheels. The robot was set to be in any one of the motion as described in Table. I along its path a reflective surfaced reference point was placed such that that the DMS senses it as obstacle only once for a rotation as shown in Fig. 3.

[Downloaded from www.aece.ro on Sunday, June 12, 2016 at 10:15:23 (UTC) by 79.113.249.254. Redistribution subject to AECE license or copyright.]

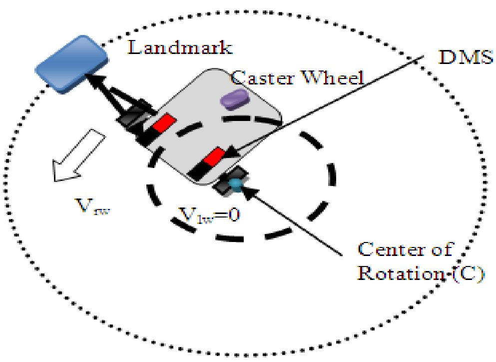

Figure 3. Robot motion for estimating the wheel slip

To measure the actual velocity of robot, a set of peak points $P = \{p_1, p_2, ...p_N\}$ with their corresponding time stamps $T_P = \{t_{p1}, t_{p2}, ...t_{pN}\}$ are acquired. A peak point is the one in which the reflection intensity is maximum as it corresponds to the possible closest distance of the robot with the reference point which can be determined by finding the local maxima point using differential function[23]. The time difference between the consecutive peak points which gives the time taken for the robot to take one full rotation was used to calculate the angular velocity ($\Delta\theta_{bar}$) of the robot as in (9) and the displacement of the robot can be calculated using the robot model in (10).

$$\Delta\theta_{bar} = \frac{2\pi}{t_{pn} - t_{p(n-1)}} \tag{9}$$

$$\begin{bmatrix} x_{rc}(n) \\ y_{rc}(n) \\ \theta_{bar}(n) \end{bmatrix} = \begin{bmatrix} L\cos\theta_{bar}(n-1) \\ L\sin\theta_{bar}(n-1) \\ \Delta\theta_{bar} \end{bmatrix} + \begin{bmatrix} x_{CR}(n) \\ y_{CR}(n) \\ \theta_{bar}(n-1) \end{bmatrix} \tag{10}$$

The actual velocity (V_{ra}) of the robot was quantified using DMS by (11),

$$V_{ra} = L\Delta\theta_{bar} \tag{11}$$

The obtained actual velocity is an averaged velocity which is up sampled by linear interpolation to match up the sampling rate of the instantaneous robot velocity measured using odometer. Such that instantaneous wheel slip velocity (V_{sc}) can be calculated from the deviation between the measured and actual robot velocity as in (12).

$$V_{sc}(n) = V_{ra}(k/N_I) - V_{rm}(n) \tag{12}$$

Where, $k = [nN_I] \in \mathrm{N}$ with N_I up-sampling rate.

B. Linear Gaussian model

In [24], non-recursive linear Gaussian model was considered to be an optimal model to capture the wheel-slip dynamics and uncertainty in wheel-slip velocity. As the wheel slip depends on the wheel velocity, the model has a biased linear relation and an unbiased Gaussian noise (ω) to account for the uncertainties as in (13).

$$V_{sc}(n) = A_o V_{ma}(n) + B_o + \omega(n) \tag{13}$$

Where, $\omega(n) \approx \mathrm{N}(0, S)$ is the Gaussian distribution modeling the slip with zero mean and covariance (S). The vectors, A_o and B_o denote the coefficient and bias, respectively. The linear trend in the acquired wheel slip data with respect to the measured wheel velocity are fitted with a first order polynomial using least square estimate [25]. The linear models thus generated provide the wheel-slip data (ω_{gs}) that can be modeled using a Gaussian distribution as described by the algorithm in Fig. 4. For each type of motion (MT), a stochastic slip compensation model was generated and the models will be switched according to the input command.

Data: V_{sc}, V_{ma}

Result: A_o, B_o, S

Initialization: $MT = \{LF \quad LR \quad RF \quad RR\}$

For each MT do

Compute: $[A_o, B_o] \leftarrow LinearFit(V_{sc}, V_{ma})$

Return: $[A_o, B_o]$

Compute: $\omega_{gs} = V_{sc} - (A_o V_{ma} + B_o)$

Compute: $[S] \leftarrow GaussianFit(\omega_{gs})$

Return: $[S]$

End

Figure 4. Wheel slip modeling algorithm

C. Terrain identifier

Identifying the type of terrain is essential for designing slip compensation schemes. As wheel slip depends primarily on the nature of the terrain in which the robot navigates [20, 22, 24], the proposed approach in this investigation selects the compensation model depending on the terrain type. The type of terrain is identified by evaluating the wheel friction from the steady state gain (K). K is calculated as a ratio of wheel velocity (V_w) to its duty ratio (D) which controls the applied voltage to the wheels at steady state as in (14). A system is said to be at steady state when there is a minimal rate change in output. Therefore, the robot is driven until the rate change in wheel velocity is minimal i.e. within a tolerance limit (ΔV_{tol}) to achieve steady state.

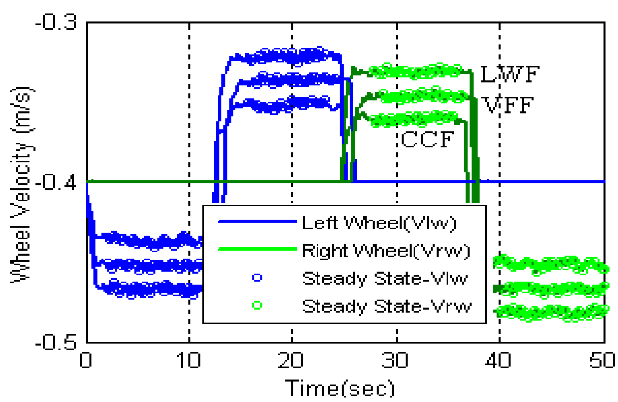

Figure 5. Robot wheel behaviour in various terrains

To evaluate the performance of the proposed terrain identifier, three terrains namely, *(i)* cement concrete floor (CCF), *(ii)* vinyl flex floor (VFF), and *(iii)* laminate wooden floor (LWF) having different wheel-terrain interactions are

[Downloaded from www.aece.ro on Sunday, June 12, 2016 at 10:15:23 (UTC) by 79.113.249.254. Redistribution subject to AECE license or copyright.]

considered for this investigation. Table I shows the various modes of operation in which the robot is subjected with a constant duty ratio to analyze the steady state behaviors of wheel in these terrains and a graph illustrating the wheel velocity is obtained as shown in Fig. 5. It is observed that the terrains can be easily identified by fixing mode specific thresholds for steady state gain (K) as shown in Fig. 6.

$$K = \left\{ \frac{V_w(n)}{D(n)} \middle| \left| V_w(n) - V_w(n-1) \right| < \Delta V_{tol} \right\} \tag{14}$$

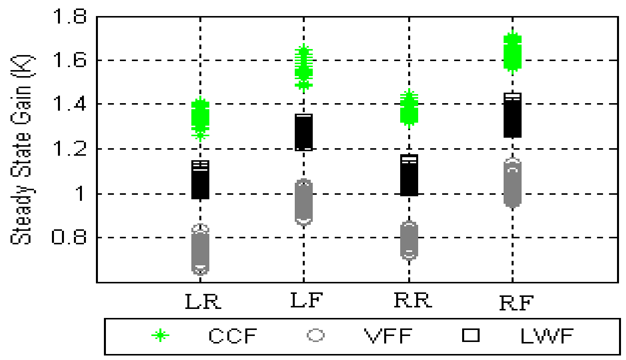

Figure 6. Steady state gain of robot wheels in various terrains

The obtained linear Gaussian models are validated using the acquired wheel slip data and its corresponding measured velocity. It is observed that the distribution of wheel slip noise follows the Gaussian relation with zero mean as shown in Fig. 7. Thus the designed models can be used to design compensation schemes for robot localization and mapping.

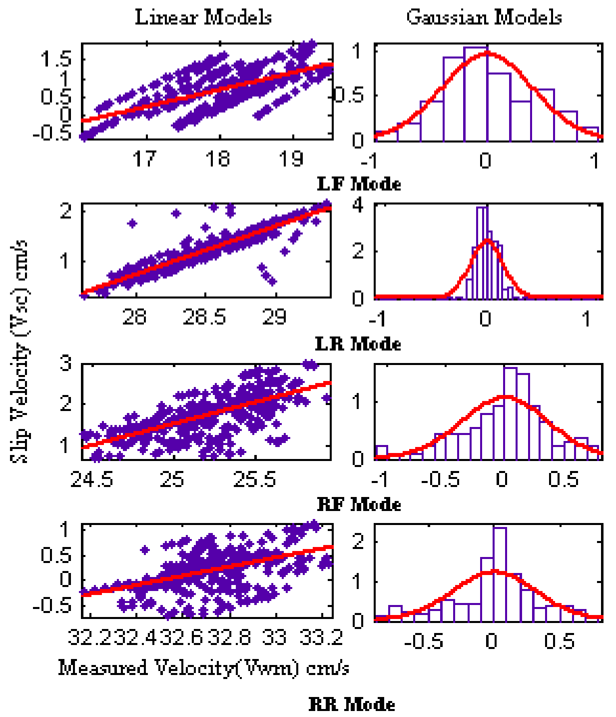

Figure 7. Linear Gaussian models for slip compensation

IV. Validation Using Map Spread Factor

The slip compensation technique requires metrics that can be used to evaluate the performance in terms of reconstructing the original map using local maps. In addition, such metric should be equally valid for robot deployments in unknown environments. Furthermore, the metric should be able to validate the algorithm in run-time. In order to suit our evaluation criteria a new metric called the map spread factor (MSF). MSF is a measure of relative occupancy of the obstacles to the free space in the retranslated map. The idea behind MSF formulation is that an inaccurate localization will lead to a spread of estimated obstacle locations and cause an increase in MSF, which indicates an increased error in retranslated map. On the other hand, an accurate localization reduces spread of obstacle position and MSF indicating an accurate mapping.

MSF can be calculated by converting the map into pixilated binary image with the specified resolution (M_r) into black and while pixels. A white pixel corresponds to an obstacle and a black indicates a free space. The acquired analog map data points from the LRF will be level shifted in order to quantize into a digital binary image. The cardinality of white pixel and black pixel are calculated, whose ratio determines the MSF as described in the flow chart at Fig. 10. In other words, MSF gives the relative degree of obstacle occupancy and free space in a map.

The MSF defined above does not directly measure the mapping efficiency, but provides a measure to study it. To obtain a measure for improvement in map reconstruction, we define the new measure called the percentage mapping improvement (M_{imp}), defined as in (15)

$$M_{imp} = \frac{MSF_u - MSF_c}{MSF_u} \times 100\% \tag{15}$$

Where (MSF_c) and (MSF_u) denote the MSF of the compensated and uncompensated localization, respectively. It is defined the ratio of difference between the MSF of uncompensated and compensated map to the MSF of uncompensated reconstructed map. It indicates the percentage reduction in MSF with introduction of proposed slip compensation technique which in turn indicates the percentage improvement in localization accuracy.

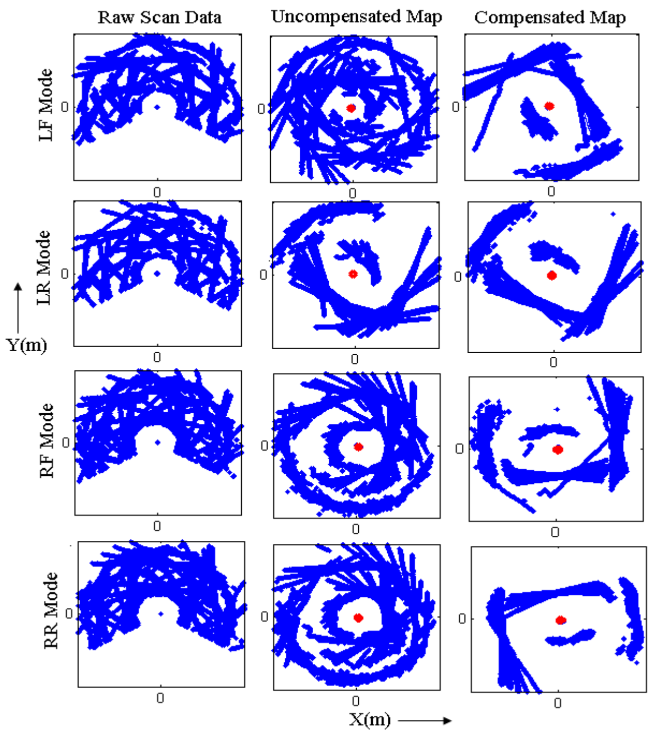

Figure 8. Peformance validation of slip compensation models

[Downloaded from www.aece.ro on Sunday, June 12, 2016 at 10:15:23 (UTC) by 79.113.249.254. Redistribution subject to AECE license or copyright.]

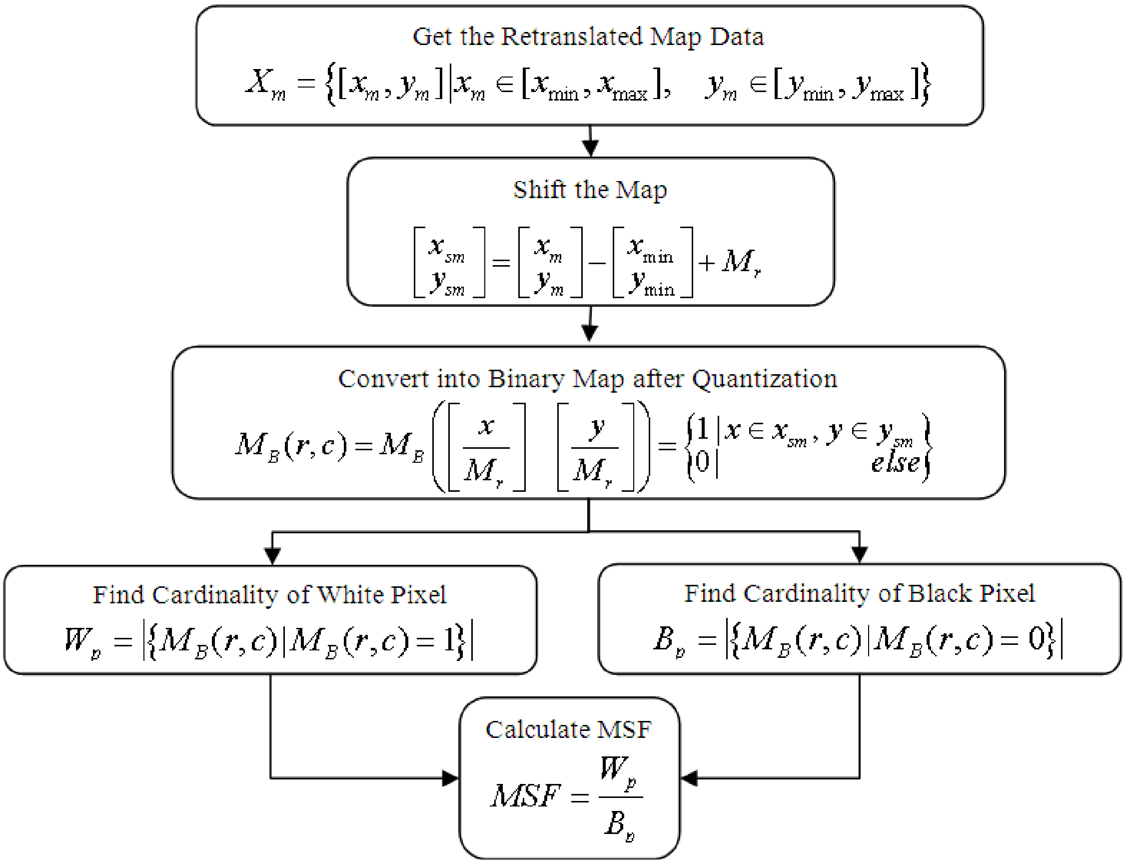

Figure 9. Flow chart to calculate MSF

V. Results and Discussions

To study the accuracy of the slip compensated localization and mapping technique, this study compares the experimental results of the uncompensated with that of the compensated mapping algorithms. As stated earlier, MSF can be used to ascertain the performance of the compensation scheme.

The performance of the proposed slip compensation technique is evaluated in three test conditions: At the first test, the slip compensation technique for each type of rotation mode is evaluated individually as shown in Fig. 8. Our results show that the proposed compensation scheme significantly improves the map reconstruction capability of the localization algorithm. In the second test, the proposed IMM based switching technique was validated based on its ability to perform localization and mapping by subjecting the robot into a random rotation motion across various terrains as shown in Fig. 10. The desired robot track have be determined based the time at which the robot switches its type of motion and the results demonstrates the ability of the proposed slip compensation to keep in track of robot as in Fig 10(c).Thus the proposed compensation scheme enhances the robot mapping capability as in Table. II.

The third test condition studies the performance of the proposed slip compensation technique when the robot is in either forward or reverse translation motion. While in forward motion, the proposed technique uses LF and RF slip compensation model to compensate the slip in left and right wheel of the robot, respectively. Whereas in reverse motion LR and RR models are used for slip compensation. The performance of these slip compensation models is evaluated by subjecting the robot to perform a loop closure in a narrow arena where translation motion is predominant. From Fig. 11, it is observed that the proposed slip compensation technique is able to reduce the deviation between the estimated and actual robot track thereby, improving the localization accuracy.

TABLE II. PERFORMANCE VALIDATION USING MSF

Type of Motion & Terrain	MSF_u	MSF_c	**%** M_{imp}
Rotation Motion in CCF	1.3410	0.3681	72.55
Rotation Motion in VFF	1.4275	0.2965	79.23
Rotation Motion in LWV	1.3381	0.3522	73.68
Translation Motion in CCF	0.6747	0.2246	66.71

A minimal spread in retranslated map indicates improved mapping performance during robot translation motion. Table. II illustrates the spread in retranslated map using an uncompensated and proposed compensation system. It is observed that in translation motion, only a smaller map spread occurs as compared with the rotation motion. This is mainly because only a smaller incremental scene change will be observed in translation motion where as a wider scene change leading to a large number of new features may be observed in rotation motion.

VI. Conclusion

Thus the article proposed stochastic slip compensation based dead-reckoning based mapping and localization algorithm. To compensate the wheel-slip, measurements were collected from the robot and the slip forces were modeled as linear Gaussian distribution. This lead to a family of hybrid models that needs to be switched based on

[Downloaded from www.aece.ro on Sunday, June 12, 2016 at 10:15:23 (UTC) by 79.113.249.254. Redistribution subject to AECE license or copyright.]

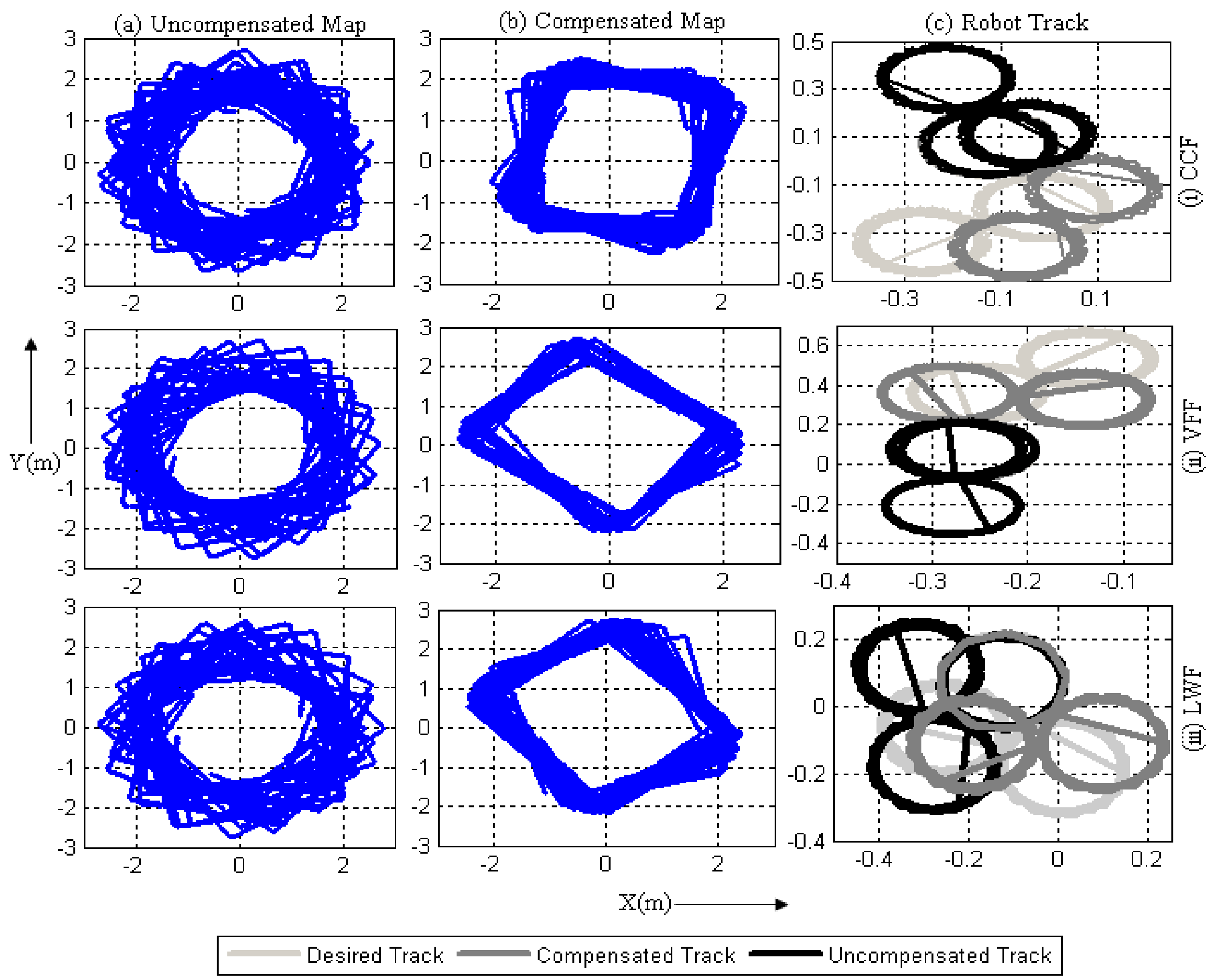

Figure 10. Localization and mapping performance of proposed technique in rotation motion across various terrains

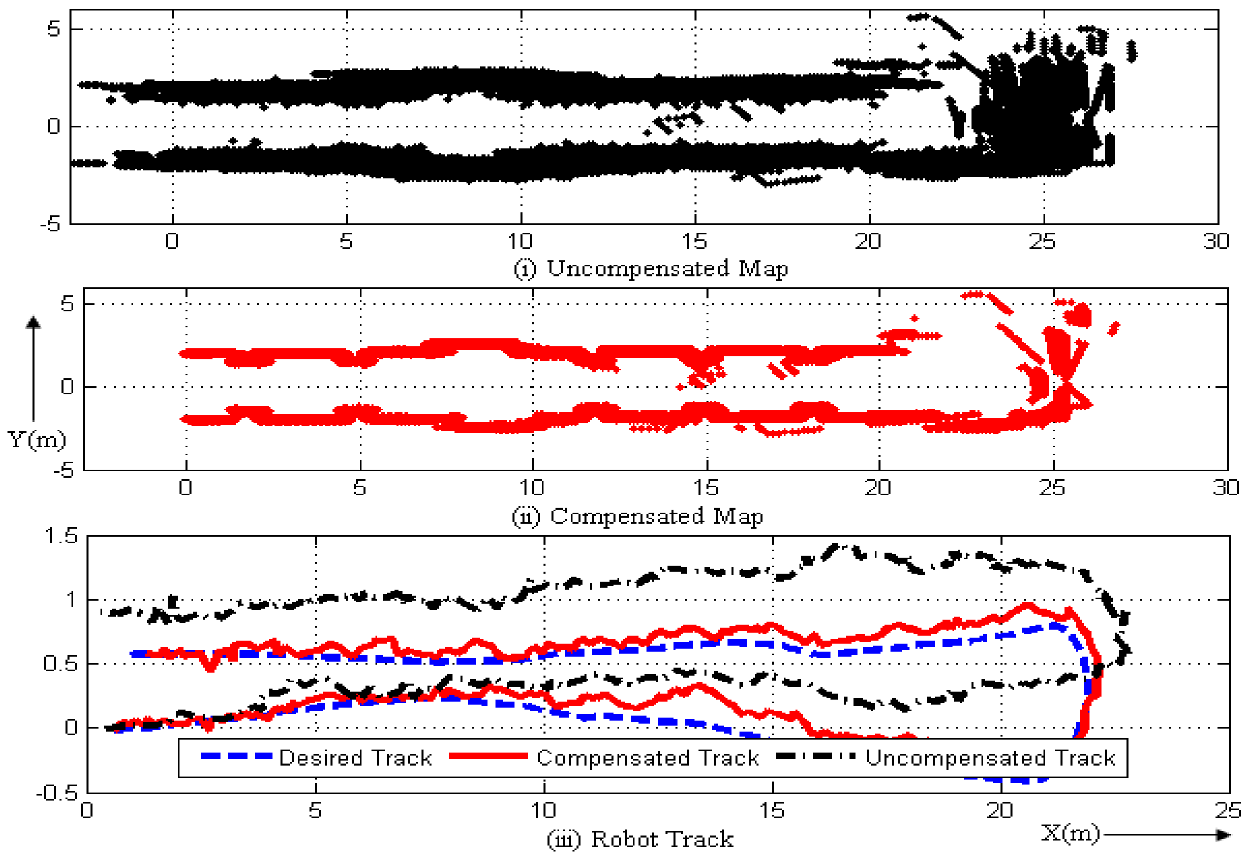

Figure 11. Localization and mapping performance of proposed technique during translation motion

[Downloaded from www.aece.ro on Sunday, June 12, 2016 at 10:15:23 (UTC) by 79.113.249.254. Redistribution subject to AECE license or copyright.]

the input command. The proposed methodology was tested using experiments on a mobile robot and our results demonstrated the enhancements achieved using the localization technique. To study the performance of the proposed mapping algorithm, a new metric called the MSF was introduced. Our results demonstrated that the proposed slip compensation scheme improved the mapping efficiency by around 72% during rotation and 67 % during translation motion over uncompensated localization and mapping.

The proposed compensation based localization method not only increases the accuracy of dead-reckoning based localization, but the realization is also simple and cheap. Extension to adaptive slip compensation technique based on terrains, robot type etc and testing the proposed methods in various deployment environments are the future course of this investigation.

REFERENCE

[1] Jaewon Seo, Hyung Keun Lee, Jang Gyu Lee,Chan Gook Park, “Lever arm compensation for GPS/INS/odometer integrated system”, International Journal of Control, Automation, and Systems, vol. 4, no. 2, pp. 247-254, April 2006, doi:10.5139/JKSAS.2013.41.6.481

[2] R. E. Precup, T. Haidegger, L. Kovács, “Stable hybrid fuzzy controller-based architecture for robotic telesurgery systems”, International Journal of Computational Intelligence and Pattern Recognition (Columbia International Publishing) ISSN 0218-0014, vol. 1, no. 1, pp. 61-76, 2014

[3] A. Tuncer, M. Yildirim, K. Erkan, "A motion planning system for mobile robots," Advances in Electrical and Computer Engineering, vol.12, no.1, pp.57-62, 2012, doi:10.4316/AECE.2012.01010

[4] C. Purcaru, R. -E. Precup, D. Iercan, L.-O. Fedorovici, R. -C. David, F. Drăgan, “Optimal robot path planning using gravitational search algorithm”, International Journal of Artificial Intelligence (CESER Publications), vol. 10, no. S13, pp. 1-20, 2013

[5] Helmick, D.M., Yang Cheng, Clouse, D., Bajracharya, M., Matthies, L.H., Roumeliotis, S.I., "Slip compensation for a Mars rover," Intelligent Robots and Systems, 2005. (IROS 2005). 2005 IEEE/RSJ International Conference on , vol., no., pp.2806,2813, 2-2 Aug. 2005 doi:10.1109/IROS.2005.1545178

[6] S. Srinivasan and R. Ayyagari, "Consensus algorithm for robotic agents over packet dropping links", 3rd International Conference on Biomedical Engineering and Informatics (BMEI), Yantai, pp. 2636-2640, 2010, doi:10.1109/BMEI.2010.5639776

[7] Silas F. R. Alves, Joao M. Rosario, Humberto Ferasoli Filho, Liz K. A. Rincon and Rosana A. T. Yamasaki, “Conceptual bases of robot navigation modeling, control and applications”, Advances in Robot Navigation, ISBN: 978-953-307-346-0, InTech, 2011, doi:10.5772/20955.

[8] Rached Dhaouadi, Ahmad Abu Hatab, “Dynamic modelling of differential-drive mobile robots using Lagrange and Newton-Euler methodologies: a unified framework”, Dhaouadi and Hatab, Adv Robot Autom 2013, 2:2, doi:10.4172/2168-9695.1000107

[9] E. I. Laftchiev, C. M. Lagoa, S. N. Brennan, "Vehicle localization using in-vehicle pitch data and dynamical models," IEEE Transactions on Intelligent Transportation Systems, vol.16, no.1, pp.206,220, Feb. 2015, doi:10.1109/TITS.2014.2330795

[10] Kichun Jo, Keounyup Chu, Myoungho Sunwoo, "Interacting multiple model filter-based sensor fusion of GPS with in-vehicle sensors for real-time vehicle positioning," IEEE Transactions on Intelligent Transportation Systems, vol.13, no.1, pp.329,343, March 2012, doi:10.1109/TITS.2011.2171033

[11] C. Pozna, R.-E. Precup, P. Földesi, “A novel pose estimation algorithm for robotic navigation”, Robotics and Autonomous Systems (Elsevier Science), vol. 63, pp. 10-21, 2015, doi:10.1016/j.robot.2014.09.034

[12] Z. Duan, Z. Cai, H. Min, “Robust dead reckoning system for mobile robots based on particle filter and raw range scan”, Sensors (Switzerland), Vol 14, Iss 9, Pages 16532-16562, 2014, doi:10.3390/s140916532.

[13] Jungwook Han, Jeonghong Park, Taeyun Kim, Jinwhan Kim, “Precision navigation and mapping under bridges with an unmanned surface vehicle”, Autonomous Robots, Volume 38, Issue 4 , pp 349-362, 2015, doi:10.1007/s10514-015-9419-2

[14] N. Y. Ko, T. Kuc, "Fusing range measurements from ultrasonic beacons and a laser range finder for localization of a mobile robot", Sensors (Switzerland), vol. 15, no. 5, pp. 11050-11075, 2015, doi:10.3390/s150511050

[15] A. W. Reza, T. T. Rui, A. S. Kausar, "An optimized indoor RFID positioning system using 3D mobility pattern," Advances in Electrical and Computer Engineering, vol.14, no.2, pp.23-28, 2014, doi:10.4316/AECE.2014.02004

[16] Hyoung-Ki Lee, Kiwan Choi, Jiyoung Park, Yeon-Ho Kim, SeokWon Bang, "Improvement of dead reckoning accuracy of a mobile robot by slip detection and compensation using multiple model approach," Intelligent Robots and Systems, 2008. IROS 2008. IEEE/RSJ International Conference on, vol., no., pp.1140,1147, 22-26 Sept. 2008. doi:10.1109/IROS.2008.4650843

[17] J. Jung, H. Lee, H. Myung,“Slip compensation of mobile robots using SVM and IMM”, Advances in Intelligent Systems and Computing - Robot Intelligence Technology and Applications 2012, Volume 208, Pages 5-12, 2013, doi:10.1007/978-3-642-37374-9_1

[18] Wei Jia, Xuan Xiao, Zhihong Deng, "Self-calibration of INS/Odometer integrated system via Kalman filter," Advanced Computational Intelligence (ICACI), 2012 IEEE Fifth International Conference on , vol., no., pp.224,228, 18-20 Oct. 2012 doi: 10.1109/ICACI.2012.6463156

[19] Z. A. Deng, Y. Hu, J. Yu, Z. Na, “Extended Kalman filter for real time indoor localization by fusing WiFi and smartphone inertial sensors”, Micromachines Vol 6, pp 523-543 2015, doi:10.3390/mi6040523

[20] Hyoungki Lee, Jongdae Jung, Kiwan Choi, Jiyoung Park, Hyun Myung, “Fuzzy-logic-assisted interacting multiple model (FLAIMM) for mobile robot localization”, Robotics and Autonomous Systems, Vol 60, Issue 12, pp 1592-1606, 2012, doi:10.1016/j.robot.2012.09.018

[21] D. F. Flippo, D. P. Miller, “Turning efficiency prediction for skid steering via single wheel testing”, Journal of Terramechanics, Vol 52, pp 23-29, 2012, doi:10.1016/j.jterra.2014.02.001

[22] J. Jia, X. Wu, W. Lv, Y. Wu, “Research on error compensation technology for vehicular dead reckoning system during accelerating or decelerating” , Yadian Yu Shengguang/Piezoelectrics and Acoustooptics, Vol 33, Issue 2, pp 210-213, 2011

[23] Carlo Arcelli, Gabriella Sanniti di Baja, “Finding local maxima in a pseudo-Euclidian distance transform”, Computer Vision, Graphics, and Image Processing, Vol 43, Issue 3, pp 361–367, 1988, doi:10.1016/0734-189X(88)90089-8

[24] Jonah H. Lee, “Statistical modeling and comparison with experimental data of tire–soil interaction for combined longitudinal and lateral slip”, Journal of Terramechanics, Vol 58, pp 11-25, 2015, doi:10.1016/j.jterra.2014.12.005

[25] So, H.C., Lin, L., “Linear least squares approach for accurate received signal strength based source localization”. IEEE Transactions on Signal Processing, Vol 59, Issue 8, pp. 4035-4040, 2011, doi:10.1109/TSP.2011.2152400

View publication stats