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Localization for Outdoor Mobile Robot Using LiDAR and RTK-GNSS/INS

Thitipong Thepsit, Poom Konghuayrob, Anakkapon Saenthon, and Sarucha Yanyong*

School of Engineering, King Mongkut's Institute of Technology Ladkrabang,
1 Chlongkrung, Ladkrabang, Bangkok 10520, Thailand

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Two types of sensors, light detection and ranging (LiDAR) and real-time kinematic of global navigation satellite system with inertial navigation system (RTK-GNSS/INS), are used for the localization of outdoor mobile robots. However, using LiDAR and RTK-GNSS/INS independently was found to be insufficient for achieving precise positioning. Therefore, a sensor fusion approach based on an adaptive-network-based fuzzy inference system (ANFIS) was implemented to enhance reliability. In this research, data from both sensors were collected to create a dataset for training with ANFIS. The findings indicated that the model derived from the fusion of these two sensors provided results that were much closer to the actual values obtained using each sensor independently. The result demonstrated the effectiveness of the ANFIS-based fusion method in terms of improving the accuracy and reliability of the positioning system for outdoor mobile robots.

1. Introduction

In an era where technology is continuously advancing, there is development in various fields including medicine, military, and agriculture and even in industry. One notable advancement is in robotics, which has seen diverse developments, from robotic arms to robot dogs, unmanned aerial vehicles, autonomous boats, and even mobile robots. Today's mobile robots have evolved into versatile tools that range from those assisting in household chores to those providing medical aid, as well as those serving in business and industrial sectors.

In the era of the Industry 4.0 revolution, mobile robots have become a crucial part of the transformation in the industrial sector. With their ability to enhance efficiency, precision, and flexibility, mobile robots are being utilized in various stages of the production process, from transporting raw materials to assembling products. Mobile robots in the industrial sector, such as automated guided vehicles, autonomous mobile robots, and collaborative robots, have transformed the way work is done in factories. What used to be heavily reliant on human labor has shifted to operations that can be automated and performed with high efficiency.[1,2] For instance, in China, companies listed in the stock exchange since 2007 have increased the

*Corresponding author: e-mail: sarucha.ya@kmitl.ac.th
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presence of robots in industrial production.(3) The use of these robots requires efficiency in various aspects to achieve optimal productivity.

In this research, we studied the positioning of outdoor mobile robots using the data obtained from positioning for an autonomous movement in the development of a prototype self-driving vehicle. Absolute localization techniques, which offer advantages such as higher accuracy, time and location independence, and external reference points, were used for positioning.(4) However, they also have drawbacks such as dependence on external factors, higher costs, and complex integration and processing. The equipment used for localization includes light detection and ranging (LiDAR) and an inertial navigation system (INS) with a global navigation satellite system (GNSS), employing real-time kinematic (RTK) GNSS/INS for localization (hereinafter, referred to as GNSS/INS), which researched in various fields to specify the precise position.(12–15)

In this study, both GNSS/INS and 3D LiDAR sensors were used for positioning at various speeds. It is projected that the use of 3D LiDAR, with its ability to generate many point clouds, offers high resolution and may be suitable for precise positioning.(5) However, the use of 3D LiDAR was limited to only capturing signals within a 90–270° range. Therefore, to increase accuracy, GNSS/INS was also employed. This combination is aimed at achieving more precise positioning. We utilized an adaptive-network-based fuzzy inference system (ANFIS) to process and integrate data from these sensors for improved localization accuracy.

In this study, ANFIS combines fuzzy logic and neural network techniques. This fusion integrates the human-like decision-making of fuzzy systems with the learning and connection structures of neural networks. This enables ANFIS to learn from data and improve its performance over time.(6) Therefore, the study involved collecting data from various speed trials to create accurate real-world comparisons. By training ANFIS with the collected data, positions could be more accurately determined, increasing the precision of the localization process. The adaptive capabilities of ANFIS allow it to refine its accuracy and reliability in various operational scenarios, making it a powerful tool for precise positioning in mobile robotics.

The paper is organized as follows: the autonomous driving vehicle used for collecting data from sensors is described, followed by the fusion of LiDAR and GNSS/INS for localization, and the experimental results from the sensor. Lastly, the conclusions of this study are presented.

2. Autonomous Driving Vehicle

In this study, the automated driving vehicle utilized is a compact golf cart designed for one person, measuring 1.4 m in length, 0.7 m in width, and 1.2 m in height. LiDAR and GNSS/INS systems are connected to a minicomputer (Intel NUC in this case) for localization purposes. LiDAR is mounted at the front of the golf cart, while GNSS/INS is installed at the position of the vehicle’s center of gravity, as depicted in Fig. 1.

The specifications of the vehicle are detailed in Table 1, which outlines both the equipment used and the characteristics of the vehicle. This table includes information such as the type and model of the vehicle, the sensors and technologies equipped (e.g., GNSS/INS and 3D LiDAR), their specifications, and other relevant features that define the vehicle’s capabilities and performance.

Fig. 1. (Color online) Small golf cart equipped with automated driving system.

Table 1
Specifications of vehicle.

Vehicle	compact golf cart designed for one person
Maximum speed	10 km/h
Size	$1.4 \times 0.7 \times 1.2$ m^3
3D LiDAR	Velodyne VLP-16
GNSS/INS	Pixhawk 2 cube orange with Here 3+ and Here+ RTK Base
Computer	Inter Core-i7 8559U

Figure 2 illustrates the connection between the vehicle's low-level and high-level systems. The low-level system includes a connection to an ARM microcontroller, which controls the steering motor's angle and speed, as well as the brushless DC (BLDC) motor. This part of the system is essential for the fundamental driving mechanics of the vehicle. On the high-level side, connections are established with 3D LiDAR and GNSS/INS systems. These components are crucial for calculating and processing the data necessary for accurate positioning.

3. Fusion Sensors

In this study, the principle of sensor fusion employed is ANFIS, in which human-like decision-making capabilities of fuzzy logic are integrated with the learning and connection structures of neural networks. This combination allows the system to learn from data and improve its performance over time. To enable this learning process, data must be collected for training the ANFIS model. The collected data help the system to accurately identify and adapt to various positioning scenarios. By training ANFIS with the collected data, the system becomes more adept at accurately determining positions, leveraging both the precise, rule-based logic of fuzzy systems and the adaptive, learning capabilities of neural networks. This results in a more robust and reliable system for localization and navigation tasks in mobile robotics.

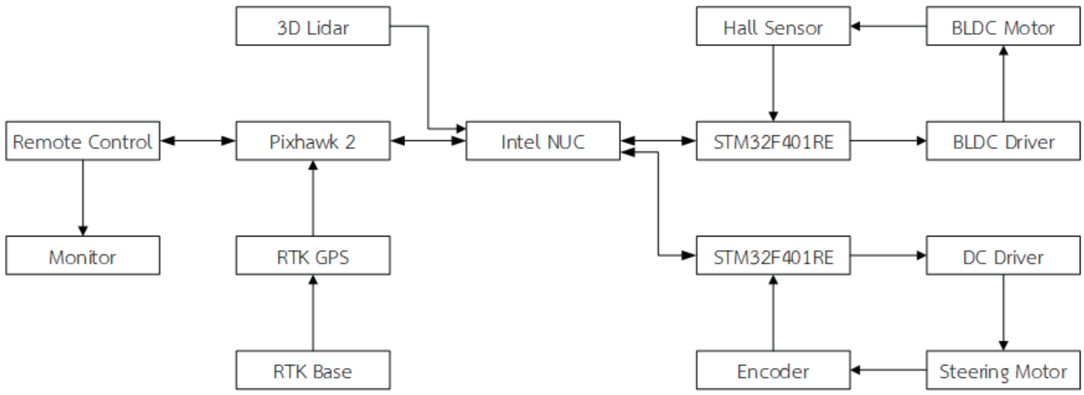


Fig. 2. Block diagram of vehicle.

3.1 Collecting data from sensors

In this experiment, data collection from sensors is performed through the Robot Operating System (ROS), an open-source framework widely used in robotics for various developmental purposes.[7] In this research, both GNSS/INS and LiDAR are integrated into the ROS framework. This integration enables the extraction of data from these sensors for two primary purposes. First is training; the data collected from GNSS/INS and LiDAR through ROS is used to train the ANFIS model. This training process allows the model to learn from real-world sensor readings, improving its ability to accurately predict and adjust to different environmental conditions and scenarios. Second is real-time positioning. Apart from training, the ROS framework also facilitates real-time data processing to carry out positioning during actual operation. This means that as the vehicle operates, ROS processes the incoming data from GNSS/INS and LiDAR, allowing the vehicle to understand its position and navigate accurately. The use of ROS in this context provides a flexible and powerful platform for developing and testing advanced robotics systems, especially those requiring complex sensor integration and data processing for autonomous operations.

In the process of collecting data from GNSS/INS for use in ROS, the primary focus is on the latitude and longitude values provided by the GNSS component. These geographical coordinates are then used to calculate precise position data,[8,9] which is essential for localization within the ROS framework.

The collection of data from the LiDAR sensor is crucial for determining odometry, which is essential for localization in the ROS environment. Mounted at the front of the vehicle, the LiDAR sensor scans the environment and collects point cloud data. The collected point cloud data comprise numerous points that represent the distances measured from the sensor to various objects in its vicinity. However, since the LiDAR sensor is front-mounted, it may inadvertently capture data from the rear. To mitigate this, the LiDAR's field of view is restricted to the 90–270° range, as illustrated in Fig. 3.

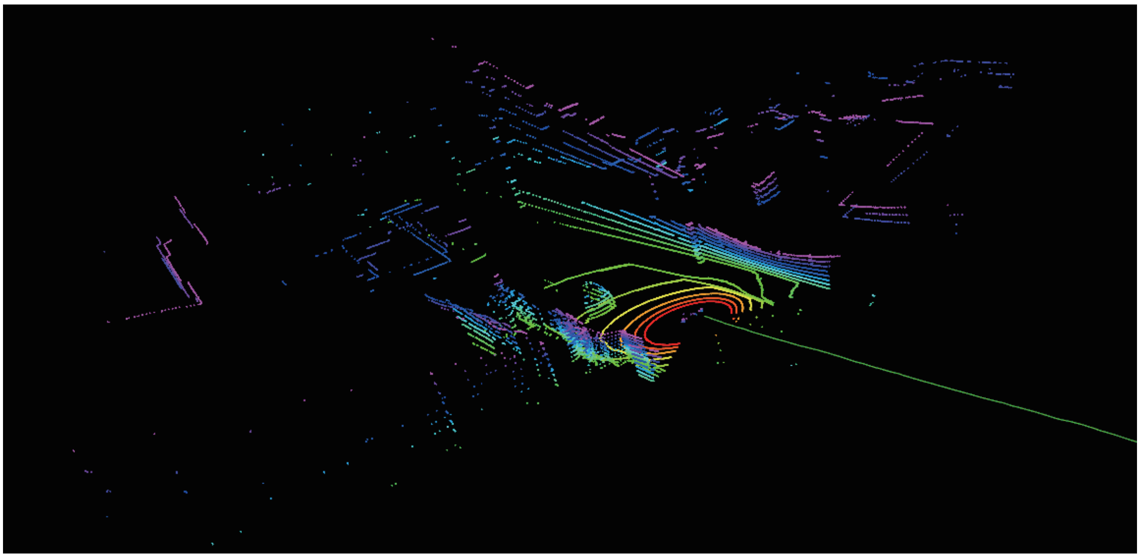


Fig. 3. (Color online) Filtering point cloud data within the 90–270° range.

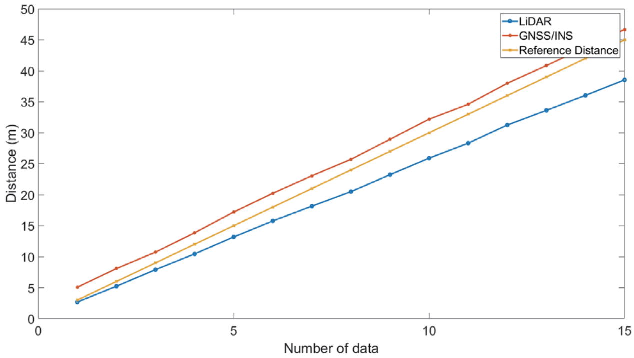
The point cloud data from LiDAR is then employed for odometry.[10,11] In this context, odometry refers to the process of determining the vehicle's position and orientation based on movement data. This is accomplished by analyzing the variations, which correspond to the vehicle's movements, in the point cloud over time. LiDAR-based odometry is a pivotal component of the vehicle's localization system and augments other data sources such as GNSS/INS. Integrating these data streams in ROS facilitates the development of a more accurate and reliable autonomous navigation system.

3.2 Training process

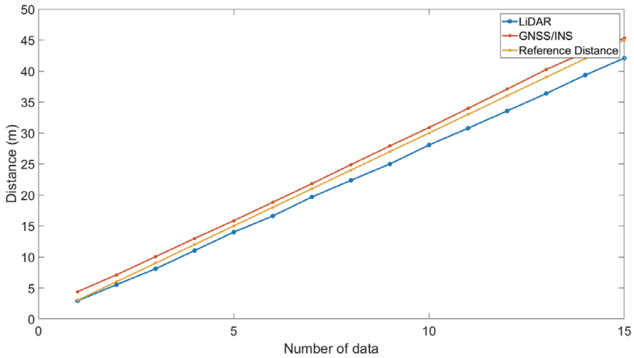
In this section, we will show the collection of values obtained from sensors, namely, LiDAR and GNSS/INS, to bring the dataset obtained from the collection of values into the training process. The values obtained from the distance measurement are shown in Fig. 4 along with the raw data from LiDAR and GNSS/INS. When compared with the actual distance, it is evident that the values from LiDAR are closer to the actual values in the initial distance range up to just before 9 m, whereas the values from GNSS/INS are farther from the real values. However, upon reaching 12 m, all values start to approach the true values. Therefore, we will integrate the LiDAR and GNSS/INS sensors through ANFIS to attain the required reliability of both sensors for further use in the next process.

Figure 4 shows the raw values of LiDAR and GNSS/INS obtained at the speeds of about (a) 1, (b) 5, and (c) 10 km/h, which is the maximum speed of the vehicle; the x-axis represents the number of recorded values and the y-axis shows the distance measured in meters.

The values to be input to the ANFIS training process will be collected from the initial range to 45 m for comparison with the actual distance. The collection will be performed once every 1 m for a total of 15 values. Then, the collection will be repeated to create a dataset for further training.



(a)



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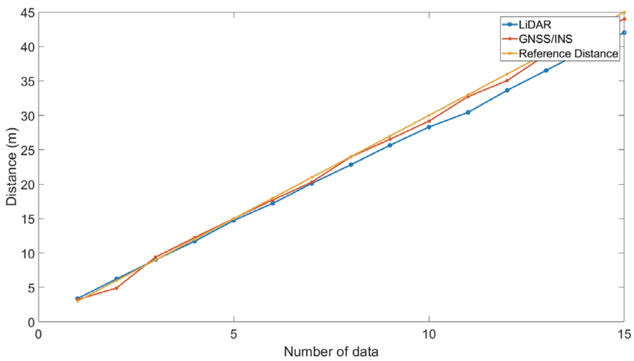


(c)

Fig. 4. (Color online) Distance measurements collected from LIDAR and GNSS/INS compared with reference data at various speeds: (a) 1, (b) 5, and (c) 10 km/h.

In the data collection process, measurements using the LiDAR and GNSS/INS sensors are conducted at King Mongkut's Institute of Technology Ladkrabang. During this process, the testing involves assessing values along two axes: the *X*- and *Y*-axes. The data are collected in a consistent manner for both axes. This approach ensures that the dataset encompasses a comprehensive understanding of the vehicle's movement and position in both horizontal dimensions, which is crucial for the accurate localization and navigation of autonomous vehicles.

In this research, ANFIS is utilized for sensor fusion. The input values for the fusion process are odometry data from both the LiDAR and GNSS/INS systems. The localization system collects odometry data from the following two sources: LiDAR odometry, which uses the point cloud information gathered by the LiDAR sensor and provides information about the vehicle's movement relative to its surroundings, and GNSS/INS odometry, which provides positional and navigational information based on satellite data and inertial measurements. These input values are then processed by ANFIS. The ANFIS model used is depicted in Fig. 5. ANFIS, by combining fuzzy logic with neural network techniques, analyzes and fuses these input values to produce a more accurate and robust estimation of the vehicle's odometry values. The output of this process is a fused positioning value representing a more precise and reliable calculation of the vehicle's position and movement obtained as a result of combining the strengths of both LiDAR and GNSS/INS data for localization. By using ANFIS for sensor integration, we aim to increase the accuracy of odometry under various conditions and environments, thereby improving the reliability and performance of the autonomous vehicle's navigation system.

In Fig. 6, which displays the dataset obtained from both the LiDAR and GNSS/INS sensors, where the x-axis represents the number of recorded values and the y-axis shows the distance measured in meters, it is observed that at a short distance from the starting point, the values from LiDAR closely match the actual distance. However, as the distance increases, the LiDAR readings start to deviate from the actual values. On the other hand, the GNSS/INS values show a consistent offset when compared with the LiDAR data. This observation indicates that while LiDAR provides high accuracy at shorter ranges, its precision diminishes over longer distances, whereas GNSS/INS maintains a consistent level of accuracy, albeit with a constant deviation

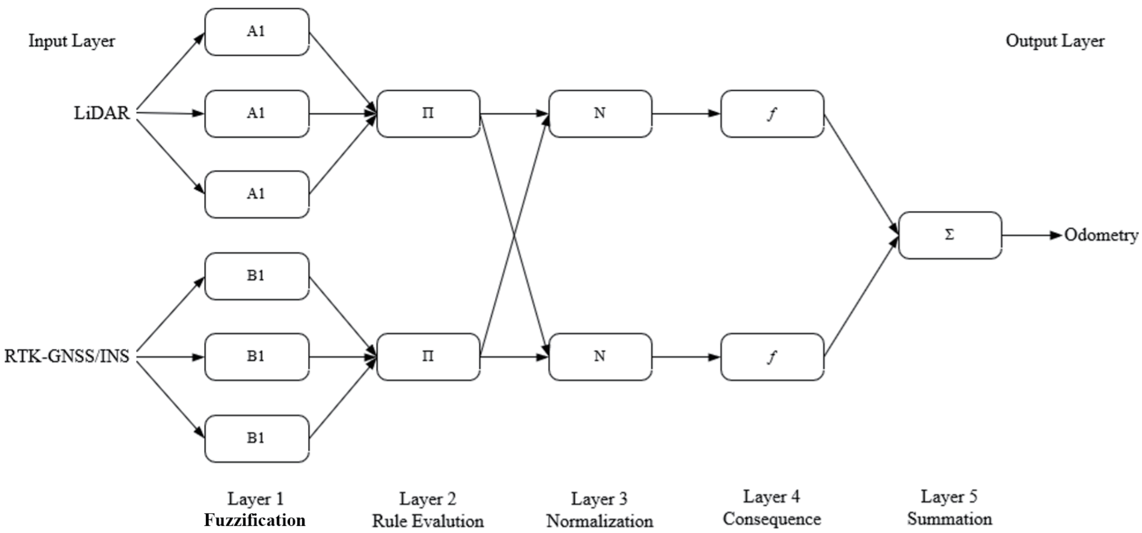


Fig. 5. ANFIS model.

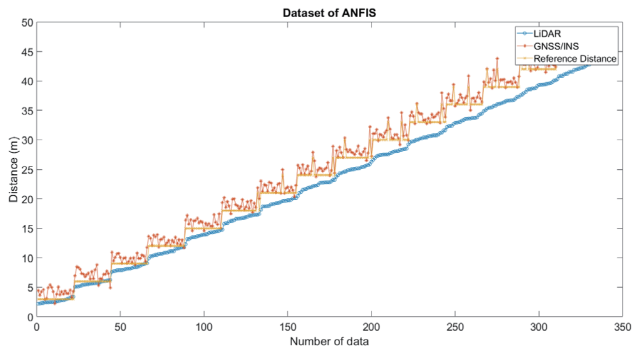


Fig. 6. (Color online) Dataset of ANFIS for training.

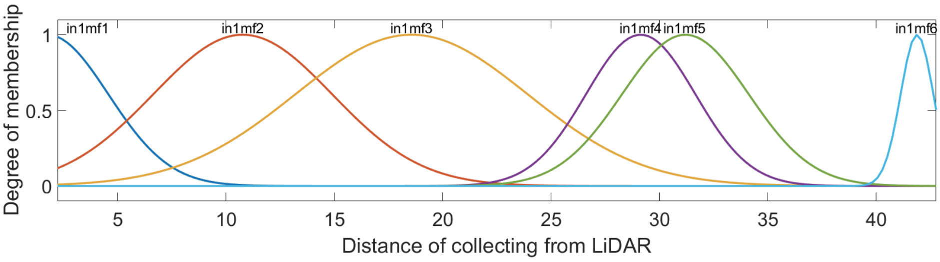
from the LiDAR readings. This type of analysis is crucial in understanding the behavior of these sensors over different distances and aids in optimizing their integration for accurate localization and navigation.

In this research, Gaussian functions were selected as the membership functions for ANFIS, as shown in Fig. 7, which has a universe of discourse of LiDAR and GNSS/INS represented by the x-axis, and the y-axis represents the degree of membership. This choice is due to the suitability of Gaussian functions for handling input values that do not change abruptly. This characteristic aligns well with the gradual changes in vehicle movement, where speed increases or decreases progressively rather than suddenly. In the context of ANFIS, Gaussian functions can adapt well during learning, providing a robust way to fuse data from LiDAR and GNSS/INS sensors. Overall, the use of Gaussian membership functions in ANFIS in this research helps to create a more accurate and reliable model for sensor fusion, accommodating the dynamic nature of vehicle movements.

From the dataset used for training in this research, it was found that the minimal training root mean square error (*RMSE*) achieved is 0.398562. An *RMSE* of 0.398562 suggests that the ANFIS model, trained with the dataset from LiDAR and GNSS/INS sensors, has achieved a reasonably good level of accuracy in predicting the correct values. The relatively low *RMSE* demonstrates the effectiveness of the sensor fusion approach using ANFIS. It indicates that combining data from LiDAR and GNSS/INS through the ANFIS model provides reliable and accurate results. Overall, achieving a minimal training *RMSE* of 0.398562 is an encouraging outcome for this research and suggests that the ANFIS-based sensor fusion method effectively captures and integrates the dynamics of the vehicle's movement as measured by the sensors.(6)

4. Experimental Results

The collection and training of values from the dataset for sensor fusion were conducted over 500 epochs across 330 datasets, resulting in a minimal training *RMSE* of approximately 0.398562. Subsequently, the trained model was tested against readings from LiDAR and GNSS/INS to compare the results of sensor fusion with the aim of evaluating the performance and effectiveness of the system. The outcomes of these tests are displayed in Figs. 8–10.



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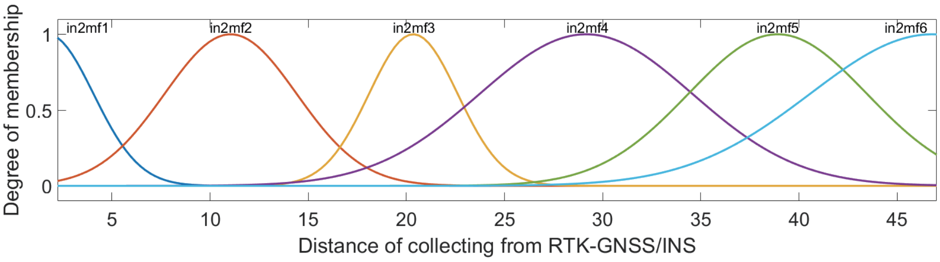
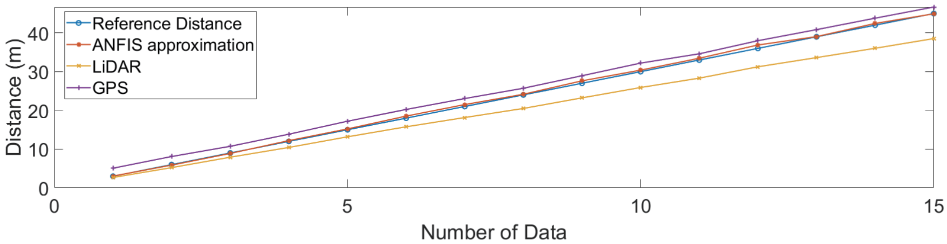


(b)

Fig. 7. (Color online) Membership functions of (a) LiDAR and (b) RTK-GNSS/INS.



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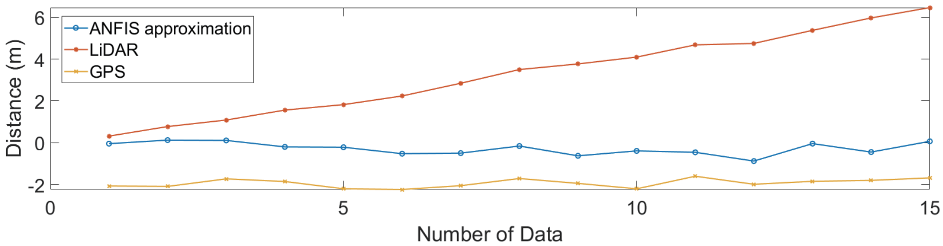
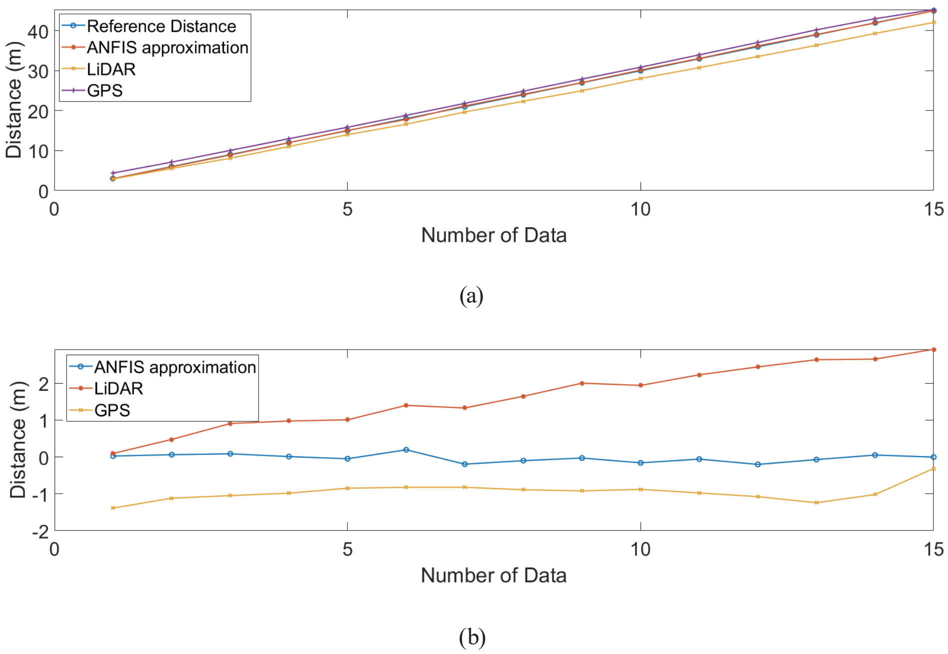


(b)

Fig. 8. (Color online) Sensor fusion at a speed of 1 km/h showing (a) efficiency and (b) the error between actual data.

Figures 8–10 show the capabilities of sensor fusion based on ANFIS compared with actual distances, where the *x*-axis represents the number of recorded values and the *y*-axis shows the distance measured in meters. The values from LiDAR and GNSS/INS at various speeds tend to diverge. The odometry values from LiDAR gradually deviate from the true values, being



(a)

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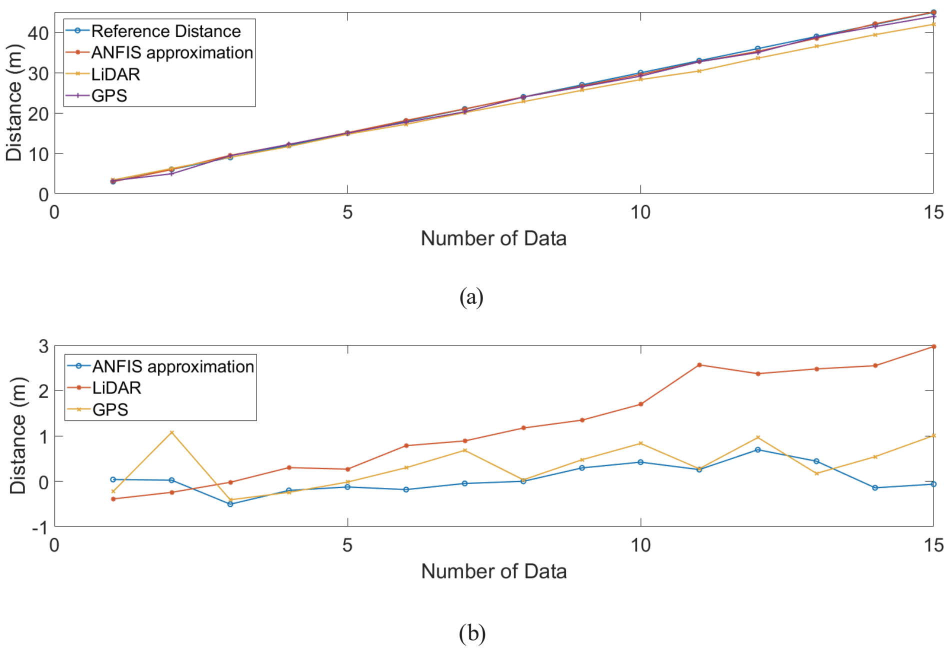
Fig. 9. (Color online) Sensor fusion at a speed of 5 km/h showing (a) efficiency and (b) the error between actual data.



(a)

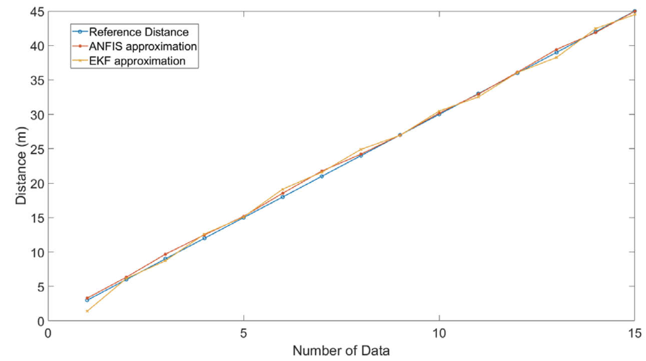
(b)

Fig. 10. (Color online) Sensor fusion at a speed of 10 km/h showing (a) efficiency and (b) the error between actual data.

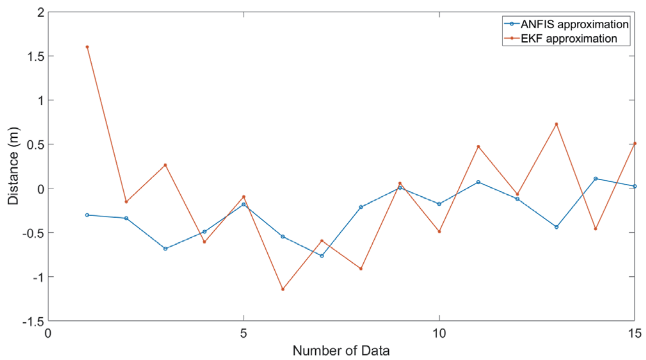
accurate only in the initial phase of the testing. However, the odometry values from GNSS/INS have a consistent deviation from the actual values with inaccuracy. When the sensor fusion based on ANFIS is utilized, it is evident that the fused sensor values are closer to the actual values, and the error compared with the real distances of LiDAR and GNSS/INS is significantly smaller. Therefore, the values from the sensor fusion based on ANFIS can be effectively used for determining the position during vehicle movement.

At the end of this study, a comparison between ANFIS and extended Kalman filter (EKF)[16,17] was conducted to analyze the improvement of robot localization accuracy. The comparative analysis is presented in Fig. 11 and Table 2.

Figure 11 and Table 2 show the values for ANFIS and EKF. The average percentage error for ANFIS is 2.58278% with a standard deviation of percentage errors at 3.09173%. On the other hand, EKF has an average percentage error of 5.67086% with a standard deviation of percentage errors at 13.31051%. As observed, ANFIS exhibits a lower average percentage error than EKF, indicating a lesser deviation from the measured values. Additionally, ANFIS also demonstrates a lower standard deviation, implying a higher measurement stability than EKF.



(a)



(b)

Fig. 11. (Color online) Comparison of sensor fusion between ANFIS and EKF showing (a) efficiency and (b) the error between actual data.

Table 2
Comparison between ANFIS and EKF.

Reference (m)	ANFIS (m)	EKF (m)	ANFIS (%error)	EKF (%error)
3	3.301841434	1.398909494	10.0613811	53.36968
6	6.338048882	6.152553211	5.63414804	2.542554
9	9.683320755	8.735862053	7.59245284	2.934866
12	12.49093677	12.60793217	4.09113977	5.066101
15	15.18193696	15.09518036	1.21291306	0.634536
18	18.54640556	19.14086377	3.03558642	6.338132
21	21.76389549	21.59279341	3.63759755	2.822826
24	24.21155327	24.90996676	0.88147197	3.791528
27	26.99368361	26.94181607	0.02339404	0.215496
30	30.17662315	30.48922456	0.58874382	1.630749
33	32.92936388	32.52696684	0.21404885	1.433434
36	36.11931053	36.06725431	0.33141814	0.186818
39	39.43728269	38.27143649	1.12123767	1.868112
42	41.88955522	42.45995099	0.26296376	1.095121
45	44.97604013	44.49019338	0.05324415	1.132904

5. Conclusions

In this study, we observed that integrating LiDAR and GNSS/INS readings into a unified dataset significantly improved localization for odometry processing in ROS using ANFIS. The process of sensor fusion using ANFIS, which achieved a minimal training *RMSE* of approximately 0.398562, yields results that align more closely with actual measurements than with the data from LiDAR and GNSS/INS separately. The results reveal that our proposed ANFIS has lower standard deviation and average error than the conventional EKF method. Therefore, the ANFIS-based sensor fusion is more suitable and stable than EKF for implementation in the localization of outdoor autonomous mobile robot applications.

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About the Authors

Thitipong Thepsit received his B.Eng. degree in electrical engineering from King Mongkut's Institute of Technology Ladkrabang (KMITL), Bangkok, Thailand, in 2021. He is currently working towards his M.Eng. degree in robotics and artificial intelligence at KMITL. His research interests are in the areas of control systems and mobile robots. (t.thepsit@gmail.com)

Poom Konghuayrob received his B.Eng., M.Eng., and Ph.D. degrees in electrical engineering from King Mongkut's Institute of Technology Ladkrabang (KMITL), Bangkok, Thailand, in 2012, 2013, and 2018, respectively. Currently, he works at KMITL in the Department of Electrical Engineering. His research interests are in the areas of robust control, DC/AC inverters, solar cell fields, and artificial intelligence. (poom.ko@kmitl.ac.th)

Anakkapon Saenthon received his B.Eng. degree in computer engineering and M.Eng. degree in electrical engineering from Naresuan University, Phitsanulok, Thailand, and Ph.D. degree in electrical engineering from King Mongkut's Institute of Technology Ladkrabang (KMITL), Bangkok, Thailand, in 2005, 2007, and 2011, respectively. Currently, he works at KMITL in the Department of Electrical Engineering. His research interests are in the areas of image processing, automatic visual inspection systems, and artificial intelligence. (anakkapon.sa@kmitl.ac.th)

Sarucha Yanyong received his B.Eng. degree in mechatronics engineering and his M.Eng. and Ph.D. degrees in electrical engineering from King Mongkut's Institute of Technology Ladkrabang (KMITL), Bangkok, Thailand, in 2012, 2014, and 2023, respectively. His research interests are in the areas of mobile robotics, machine learning, control systems, and artificial intelligence. (sarucha.ya@kmitl.ac.th)