Journal of the Korean Society of Surveying, Geodesy, Photogrammetry and Cartography
Vol. 39, No. 5, 289-295, 2021
https://doi.org/10.7848/ksgpc.2021.39.5.289

ISSN 1598-4850(Print)
ISSN 2288-260X(Online)
Original article

Precision Analysis of NARX-based Vehicle Positioning Algorithm in GNSS Disconnected Area

Lee, Yong[1)] · Kwon, Jay Hyoun[2)]

Abstract

Recently, owing to the development of autonomous vehicles, research on precisely determining the position of a moving object has been actively conducted. Previous research mainly used the fusion of GNSS/IMU (Global Positioning System / Inertial Navigation System) and sensors attached to the vehicle through a Kalman filter. However, in recent years, new technologies have been used to determine the location of a moving object owing to the improvement in computing power and the advent of deep learning. Various techniques using RNN (Recurrent Neural Network), LSTM (Long Short-Term Memory), and NARX (Nonlinear Auto-Regressive eXogenous model) exist for such learning-based positioning methods.

The purpose of this study is to compare the precision of existing filter-based sensor fusion technology and the NARX-based method in case of GNSS signal blockages using simulation data. When the filter-based sensor integration technology was used, an average horizontal position error of 112.8 m occurred during 60 seconds of GNSS signal outages. The same experiment was performed 100 times using the NARX. Among them, an improvement in precision was confirmed in approximately 20% of the experimental results. The horizontal position accuracy was 22.65 m, which was confirmed to be better than that of the filter-based fusion technique.

Keywords : Deep Learning, NARX, Sensor fusion, GNSS Blockages, Vehicle Positioning System

1. Introduction

Traditional vehicle positioning systems combine the data obtained from the sensor with a filter to calculate a navigation solution. Data obtained through GNSS and inertial sensors are typically used. To acquire more information various studies have been conducted to improve positioning precision by attaching various sensors, such as cameras and automobile internal sensors. However, recently, with the advent of deep learning, research on positioning through deep learning is being actively conducted(Baker and Åkerblad, 2018; Aslinezhad *et al.*, 2020). In this study, the precision of positioning technology through deep learning was compared with existing mobile positioning technology through filter fusion. The aim was to compare the performance of each technology in case of GNSS disconnection using simulation data.

Dai *et al.*(2020) performed a study to estimate the position and velocity errors in a situation where the GNSS signal was disconnected by combining IMU and GNSS using an RNN. This study was conducted to compare positioning errors with the extended Kalman filter. When performing learning using RNN, the variation in velocity and change in attitude, position

Received 2021. 09. 24, Revised 2021. 10. 06, Accepted 2021. 10. 13

1) Member, Ph.D. student, Dept. of Geoinformaticts, University of Seoul(E-mail: acce00@uos.ac.kr)
2) Corresponding Author, Member, Professor, Dept. of Geoinformaticts, University of Seoul(E-mail: jkwon@uos.ac.kr)

error, and velocity error were used as input data, and position error and velocity error were estimated as output data. When positioning was performed based on the extended Kalman filter when the GNSS signal cutoff for 15 seconds, a position error of approximately 15 m was found. When the position error was estimated using RNN, the horizontal position accuracy of approximately 6 m was observed.

Li *et al.*(2019) conducted a study using NARX to combine GNSS, MEMS (Micro Electro Mechanical Systems) IMU, and electronic compass. In this study, NARX and Kalman filters were bonded to compensate for the position error of the IMU that occurred during GNSS signal disconnection. The acceleration, angular velocity, and measurement time calculated by the IMU were used as input data for learning. When the GNSS signal is available, learning can be performed using the position error as a target. When the GNSS signal is disconnected, an algorithm was developed that compensates for the error of the Kalman filter's error by predicting the position using the acceleration, angular velocity, and measurement time calculated by the IMU as inputs. In this study, the positioning performance was evaluated in case of GNSS disconnection for 45 seconds. When only the Kalman filter was used, a horizontal position error of approximately 80 m occurred. By using NARX additionally, the performance was improved to approximately 15.8 m.

Al-Bistar and Gavrilov(2021) conducted a study to estimate the position and velocity errors in GNSS-disconnected sections using NARX. In this study, NARX was used to overcome the limitations of existing filter-based sensor fusion methods for GNSS disconnected areas. Learning was performed assuming that the GNSS signal was blocked repeatedly. Position and velocity errors were used as the target data. By adding the calculated position error and velocity error from learning to the existing filter, the horizontal position error of approximately 34 m in case of a 60 seconds GNSS signal disconnection was improved to of 9.6 m.

2. Methodology

2.1 NARX

Neural networks can learn or approximate arbitrary nonlinear functions through their excellent mapping ability, and are useful for modeling nonlinear systems. The NARX model is generally constructed based on the ARX (Auto-Regressive with eXternal input) model used for time series modeling, and the mathematical definition of the NARX model can be expressed as Eq. (1) below:

$$y(t)=f(y(t-1),y(t-2),\cdots,y(t-n),x(t-1),x(t-2),\cdots,x(t-n))\quad(1)$$

where, x and y denote the input and output, respectively, and n denotes the order of the output.

The NARX model is a neural network circuit that considers feedback and is mainly used for time-series modeling. The structure of the NARX model used in this study is shown in Fig. 1, consisting of a hidden layer and an output layer. To calculate $y(t)$, which is an output, in addition to the input value x, the output values $y(t-1)$, $y(t-2)$, and $y(t-n)$ of the previous order are used again as inputs.

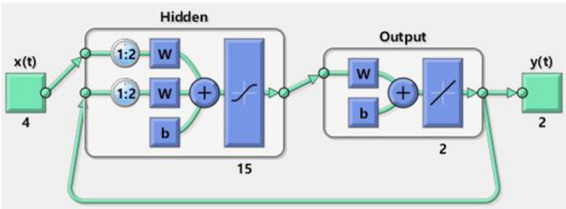

Fig. 1. Structure of NARX net

In the NARX model used in this study, the number of hidden nodes in the hidden layer was set to 15. This was determined through empirical experiments. When the number of hidden nodes was less than eight, a value utterly different from the target value was calculated through learning. However, as the number of nodes increased, the operation time required increased rapidly. Thus, the number of hidden nodes was set to 15 in the experiments in this study. The input delay was 2, and the maximum number of training iterations was 1000.

In the NARX training model used in this study, four data were input to gain two outputs. The input data used for learning comprised the x-and y-axis acceleration, z-axis angular velocity data, and yaw, each of them including errors. The training was performed by targeting a two-dimensional position that did not contain any error.

2.2 Simulation data

In this study, the positioning precision of extended Kalman and NARX was compared. After combining the GNSS/IMU data using the extended Kalman filter and NARX, the combined results were compared with the reference data. The extended Kalman filter-based positioning algorithm used in this study was developed in previous studies(Lee and Kwon, 2018). It‘s error state vector consist of position, attitude, velocity, gyro bias, and accelerometer bias. The filter based GNSS/IMU combination used in this study was found to have a precision of about 20 m in 30 seconds of GNSS outages.

First, 100 Hz interval IMU data and 1 Hz GPS data without error were generated. Then the simulated data were generated after adding the sensor error. The specifications of the IMU sensor and the error of the GNSS data are shown in the tables 1 and 2. The simulated IMU data were generated based on the MEMS level.

Table 1. IMU specification of simulation data

	Accelerometer	Gyroscope
Noise density	$150\mu g/\sqrt{Hz}$	$0.015^{\circ}/s/\sqrt{Hz}$
Bias instability	$0.05\,m/s^2$	0.05 °/s
Axes misalignment	0.5 °	0.01 °

Table 2. GNSS position and velocity error of simulation data

Velocity	Position
±0.02 m/s	±0.5 m

The simulation data were for three laps of track-type driving for 20 min. The speed of the vehicle was 20 m/s. Because driving was on a track, there were straight and curved sections. The speed was almost constant, but there was a slight change in speed at the curved sections. In this route, there were 13 zones where the GNSS signal was intentionally blocked for 60 seconds. In the Fig. 2, the green line presents the reference data without error. The blue line is the filter-based GNSS/IMU integration result using simulation data with error.

Approximately 77% of the simulation data were used for training. All data from the start of driving to before the 11th GNSS signal blockage were used for learning. At the 11th, 12th, and 13th GNSS signal blocks, two-dimensional position prediction was performed when the GNSS signal blockage occurred. When the GNSS signal was available again, additional training was performed. Learning was conducted 100 times using the same data and the same training parameters. All learning results were compared with the reference data.

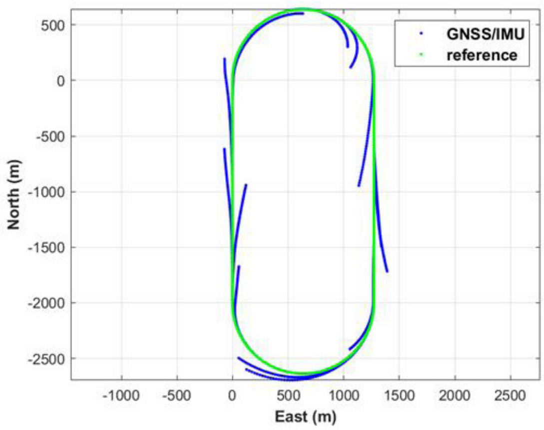

Fig. 2. Horizontal position of simulation data

3. Performance Evaluation

The performance evaluation of the filter-based positioning algorithm and the learning-based positioning algorithm was performed by comparing the horizontal position error at the last point of GNSS outages. Since the filter- based GNSS/IMU combination performs dead reckoning in the GNSS disconnection situation, position error increases rapidly over time. Therefore the position at the last epoch of GNSS outages was compared. Additionally, the standard deviation of the horizontal position error in the GNSS outages was compared. Performance analysis was conducted in three zones, assuming a GNSS signal disconnection for 60 seconds.

The performance in the first prediction section, the 11th GNSS signal blockage section, is as follows: at the last epoch of the GNSS signal blockage, the horizontal position error of the GNSS/IMU combination using the filter was approximately 135.9 m. Among the 100 NARX learning results, 25 training results had higher precision than the filter-based GNSS/IMU combined result.

The Fig. 3 shows the horizontal position error of 25 experiments with a lower horizontal position error than the filter-based combination result. The red line is the average value of 25 results, which is 29.46 m. Among them, the result with the lowest horizontal position error was confirmed to have an error of 1.7 m (Fig. 4).

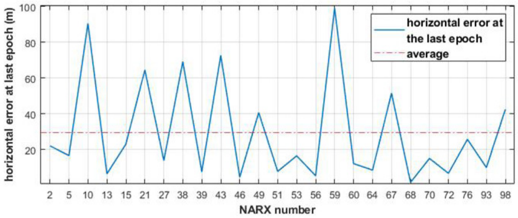

Fig. 3. Horizontal error at last epoch of GNSS outage in 11th GNSS blockage

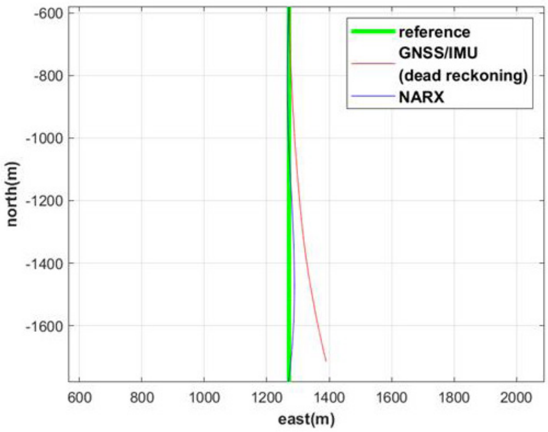

Fig. 4. The best prediction result in 11th GNSS blockage

The standard deviation of the horizontal position error of the filter-based GNSS/IMU combination is 39.10 m in the 11th GNSS outages. The standard deviation of horizontal position error for the entire GNSS outages for the above 25 experiments among the NARX-based experiments is shown in the Fig. 5. The average of the standard deviation of 25 experiments is 9.89 m. The minimum value was 0.919 m and the maximum value was 27.09 m.

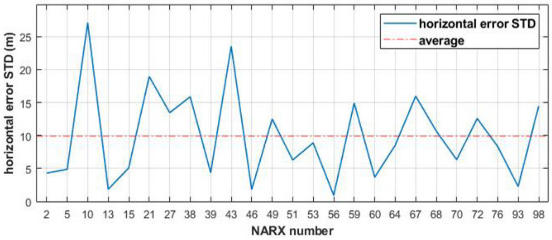

Fig. 5. STD of Horizontal error at GNSS outage in 11th GNSS blockage

The horizontal position error of the GNSS/IMU combination using the filter at the last epoch of the 12th GNSS signal blockage was 130.4 m. Among 100 NARX learning results, a total of 27 results shows better precision than the filter-based GNSS/IMU combination result. Fig. 6 shows the horizontal position error at the last epoch of GNSS outages for 27 experimental results in the 12th GNSS signal disconnection. The average horizontal position error at the end of the GNSS disconnection of the experiment with higher precision than the result using the filter was 19.12 m, represented by the red line.

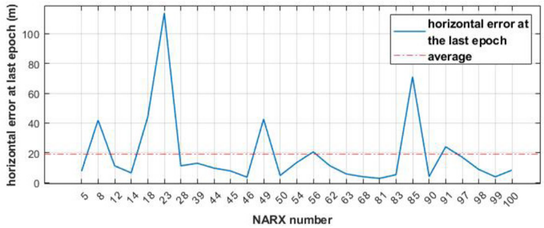

Fig. 6. Horizontal error at last epoch of GNSS outage in 12th GNSS blockage

Among them, it is confirmed that the result of the 81st experiment provided the best prediction, with a horizontal position error of 2.7 m at the 12th blockage of signal. The results of the 12th GNSS signal blockage are shown in the Fig. 7.

In 12th GNSS outages, the standard deviation of the horizontal position error of the filter-based GNSS/IMU combination is 34.36 m. The the standard deviation of horizontal error in the GNSS outages for the above 27 NARX-based experiments are shown in the Fig. 8. The average of standard deviation for 27 experiments was 5.50

m, the minimum value was 1.30 m, and the maximum value was 21.76 m.

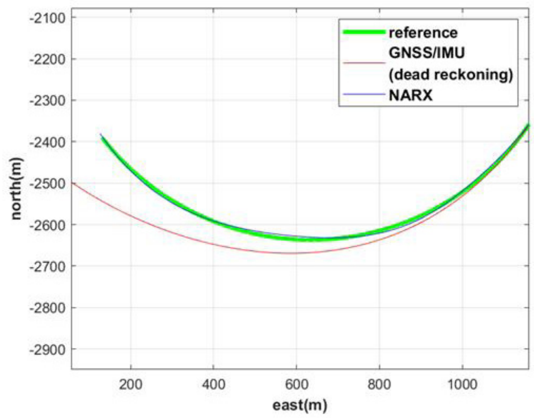

Fig. 7. The best prediction result in 12th GNSS blockage

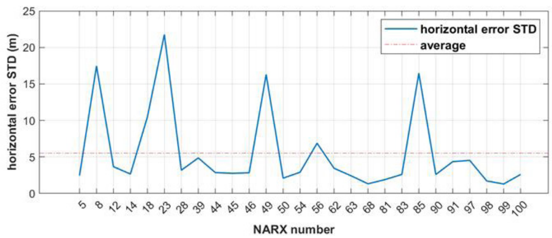

Fig. 8. STD of Horizontal error at GNSS outage in 12th GNSS blockage

The horizontal position error of the GNSS/IMU combination using the filter at the last position of the 13th GNSS signal disconnection was 72.2 m. Among the 100 NARX learning results, 14 experiments had a higher precision than the filter-based GNSS/IMU combination. The average horizontal position error of the 14 experiments was approximately 20.9 m (Fig. 9). It was found that the horizontal position error of the 52nd experiment was the lowest at 0.4 m (Fig. 10).

The standard deviation of the position error of the filter-based GNSS/IMU combination in the 13th signal outages was 23.72 m. For the above 14 NARX experiments, The standard deviation of the horizontal position error in the GNSS outages is shown in the Fig. 11. The average of standard deviation was 6.42 m, the minimum value was 2.26 m, and the maximum value was 14.38 m.

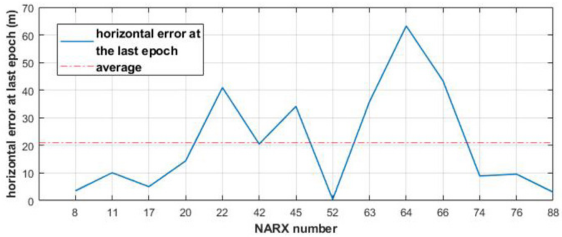

Fig. 9. Horizontal error at last epoch of GNSS outage in 13th GNSS blockage

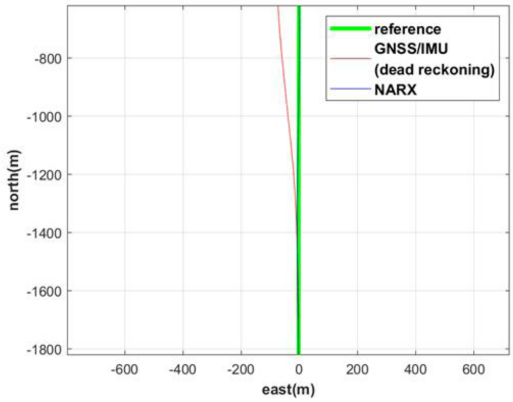

Fig. 10. The best prediction result in 13th GNSS blockage

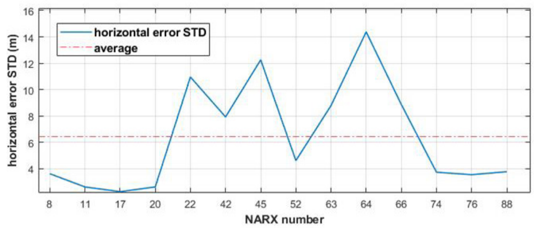

Fig. 11. STD of Horizontal error at GNSS outage in 13th GNSS blockage

At the 11th, 12th, and 13th GNSS blockages, approximately 20 learning results showed better positioning accuracy than the filter-based GNSS/IMU results. The table 3 shows the number of experiments in which the position was determined to be more precise than the existing filter-based positioning technology among 100 learning experiments in the 11th to 13th GNSS blockages.

The GNSS/IMU combination perform dead reckoning using only the IMU in the GNSS signal disconnection area.

Table 3. Comparison of horizontal position error between filter-based fusion and NARX-based method

Type		11th blockage	12th blockage	13th blockage
Filter-based fusion method	Horizontal position error at the last epoch of GNSS outages	135.89 m	130.42 m	72.24 m
	STD of horizontal position error	39.10 m	34.36 m	23.72 m
NARX-based fusion method	The number of experiments with better accuracy than the filter-based sensor fusion method	25	27	14
	Average of horizontal position error at the last epoch of GNSS outages	29.46 m	19.12 m	20.93 m
	Average of STD of horizontal position error in GNSS outages	9.89 m	5.50 m	6.43 m

Since the error of the accelerometer and the gyroscope accumulates over time, the position error increases rapidly. In the NARX-based algorithm, only information that can be obtained from the IMU was used as input data. NARX-based learning has the advantage of being able to predict regardless of whether or not GNSS is disconnected because data obtained from GNSS are not used as input data. Therefore, if learning is performed properly, it seems that positioning is possible regardless of GNSS or not.

However, in the remaining results, it was confirmed that the horizontal position error was rather large at the last time of GNSS blockage compared to that for the filter-based GNSS/IMU combined results. If learning is not performed correctly, there are cases when the results do not converge or vibrate, resulting in a two-dimensional position error of several kilometers. This is a case in which the position estimation accuracy is very low despite reaching the maximum number of iterations. Additionally, the NARX-based positioning results, which showed better results than the filter-based GNSS/IMU combination, also showed a large deviation in the values in the same disconnection section. Therefore, additional research should be conducted to produce stable NARX-based positioning method.

4. Summary and Conclusion

This study compared the positioning precision of the existing filter-based sensor fusion technique developed in previous studies and the learning-based sensor fusion technique. Using simulation data, a precision comparison was performed for cases of GNSS signal blockages.

In the case of three GNSS signal blockages, the filter-based positioning method showed an average position error of 112.8 m. As a result of repeatedly performing 100 learning experiments, it was confirmed that approximately 20% of the results were more precisely positioned than those positioned by the existing filter-based fusion technique. Approximately 20% of the results showed a two-dimensional position error of approximately 22.65 m during the three GNSS signal blockages.

However, the rest of the learning results confirmed that the horizontal position error was rather large by the time that GNSS signal was restored compared to the filter-based combination result. If learning is not performed correctly, there are cases when the results do not converge or vibrate, resulting in a two-dimensional position error of several kilometers. Since the input value and the target value are all the same in 100 experiments, it seems necessary to analyze the effect of initial weights and bias on training convergence. Therefore, additional research on the conditions for improving the positioning performance of NARX and should be conducted.

Acknowledgment

This work was supported by the 2020 Research Fund of the University of Seoul.

References

Al-Bistar, N., and Gavrilov, A. (2021), A New Method for Compensating the Errors of Integrated Navigation Systems Using Artificial Neural Networks. *Measurement*, Vol. 168, pp. 1-12.

Aslinezhad, M., Malekijavan, A., and Abbasi, P. (2020), ANN-assisted Robust GPS/INS Information Fusion to Bridge GPS Outage, *EURASIP Journal on Wireless Communications and Networking*, Vol. 2020, No. 1, pp. 1-18.

Baker, T. and Åkerblad, M. (2018), *A Study on Long Short-term Memory Networks Applied to Local Positioning*, Master's thesis, Royal Institute of Technology, Stockholm, Sweden, 77p.

Dai, H.F., Bian, H.W., Wang, R.Y., & Ma, H. (2020), An INS/GNSS Integrated Navigation in GNSS Denied Environment using Recurrent Neural Network. *Defence technology*, Vol. 16, No. 2, pp. 334-340.

Lee, Y., and Kwon J.H. (2018), Performance Analysis of the GNSS/MEMS-IMU/on-Board Vehicle sensor/magnetometer-based Positioning System during GNSS Signal Blockage, *International Journal of Urban Sciences* , Vol. 23, No. 3, pp. 1-10.

Li, X., Chen, W., Chan, C., Li, B., and Song, X. (2019). Multi-sensor Fusion Methodology for Enhanced Land Vehicle Positioning. *Information Fusion*, Vol. 46, pp. 51-62.