NLOS Satellite Detection Using Fish-Eye Camera for Improving GNSS Positioning Accuracy — Further Results

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Abstract

In this paper, for the GNSS (Global Navigation Satellite System) positioning, based on the method to efficiently distinguish non-line-of-sight (NLOS) signals from line-of-sight (LOS) signals [1], and show further results of actual GNSS positioning in various circumstances.

1 Introduction

GNSS is widely used because it can perform highly accurate positioning, however the accuracy can be degraded in places where radio waves are difficult to reach such as urban areas and mountainous areas.

Fig. 1: Multipath Signal

Fig. 1 shows the multipath signals in urban areas. GNSS signals tend to reflect on glass, metals, wet surfaces. In the urban area, in addition to signals received directly from satellites, the GNSS receiver may also receive signals reflected on buildings, walls, grounds, etc. This signal is called “multipath signal”. Especially multipath signals received from satellites which are obstructed by obstacles and can not be directly received are called NLOS signals. They can not be perfectly corrected even if multipath mitigation techniques are applied [2]. In such case, the positioning accuracy in urban areas is greatly degraded. In this research, we aim to improve the positioning accuracy by estimating the NLOS satellites and excluding or de-weighting them in the positioning calculation.

2 Methods

According to our previous research [1], the NLOS satellite estimation method was developed by using a fish-eye camera. Fig. 2 shows the flow chart of the algorithm proposed in [1].

First, we set omnidirectional fish-eye camera with optical axis aligned to the zenith, and divide the sky and obstacles into regions by using image processing for the images taken by the fish-eye camera. Next, we calculate the elevation angle and the azimuth angle using the satellite position and the approximated receiver position calculated from the data obtained from the satellite, and plot the satellite position on the image after region division while taking the camera projection method into consideration. Finally, the satellite in the obstacle region is estimated as the NLOS satellite and
excluded from the positioning calculation. However, it is also reported that sometimes the number of satellites will easily be less than the minimum requirement for the position calculation, that is four satellites, in severe circumstances. Therefore, in this paper, we try to develop the method can continue to provide accurate position information by not only excluding NLOS satellites but also methods to de-weight them. Fig. 3 shows an example of the detected NLOS Satellites. The left figure in Fig. 3 shows the satellites' positions with satellite identifier such as “G12”. In the right figure, satellites G31 and R11 are detected as the NLOS satellites.

Fig. 3: NLOS Satellite Detection

3 Image Processing

3.1 FCN

In [1], FCN (Fully Convolution Networks) [3] which is a method of semantic segmentation is used for discrimination of sky area. FCN is an extension of the classification method CNN (Convolutional Neural Network) to the pixel level. This method can be efficiently applied when there exist disturbances such as cloud movement and car body shaking, and it is possible to discriminate the sky region even in such situations, so we consider that the proposed method can discriminate the sky region more accurately in various circumstances. The model applied in this research is so-called fcn8s with the highest accuracy among the three methods described in the paper [3]. The structure and parameters for fcn8s applied in this research are summarized in our previous work[1].

We create teacher data using index color with reference to Visual Object Classes Challenge 2012 [6]. Fig. 4 shows an example of teacher data. The right figure in Fig. 4 shows that the red area is the sky area, and the black area is the obstacle area. The teacher image created with index colors is composed of the color map and corresponding indexes, therefore there is an advantage that it is easy to read the index data for classification.

3.2 Projective Transformation

The lens of the fish-eye camera is an orthographic projection therefore we need to transform from equidistant projection to orthogonal projection in order to plot the satellite position on the image obtained from the fish-eye camera. The method for the transformation is also detailed in our previous work[1].

4 Experimental Results

4.1 Semantic Segmentation

In this experiment, the model is learned by using the sky image and teacher data, and we examine the output accuracy of the inference result. Table 1 shows the experimental conditions.

| Location          | Kobe City |
|-------------------|-----------|
| Model             | fcn8s     |
| Model Parameter   | VGG16     |
| epoch             | 100       |
| Camera            | α5100 (SONY) |
| Lens              | MADOKAI80 (YASUHARA) |
| Angle of view     | 180°      |
| Projection method | Orthographic projection |

We prepared 25 cloudy images taken on July05, 2019 and 25 sunny images taken on September03, 2019, and expanded these data. We rotated and reversed the images at random 25 times for data augmentation. We set the number of epochs to 100 so that it can be learned sufficiently.

Fig. 5, 6 and 7 show the inference result. The left figures in Fig. 5, 6 and 7 show the unlearned images, and the right figures show the inference results. The white area is the sky area, and the black area is the obstacle area.

From Fig. 5 and 6, it can be seen that we can infer the sky area with high accuracy. From Fig. 7, is an example of failure due to insufficient teacher data of traffic light and Electric light. It is considered that the accuracy can be improved by increasing teacher data.

4.2 Positioning

In this experiment, we estimate NLOS satellites using inference images obtained by semantic segmenta-
tion and exclude or de-weight them from the positioning calculation. Since the purpose of this experiment is to evaluate the accuracy improvement when excluding or de-weighting NLOS satellites, we apply the single frequency point positioning method based on the least squares estimation, which is the simplest positioning method [7, 8]. The single frequency point positioning (or standard point positioning; SPP) is a positioning technique that receives a signal from a satellite with a receiver and estimates the coordinates of the receiver from the geometric distance between the satellite and the receiver. The geometric distance can be measured as the receiver data which is called C/A code pseudorange and the broadcast ephemeris [7]. According to [7], the measurement equation of the pseudorange for satellite “p” and receiver “u” is as follows.

\[
\rho_u^p = \sqrt{(x_u - x^p)^2 + (y_u - y^p)^2 + (z_u - z^p)^2} + c\delta t_u + e_u^p
\]

where \([x_u, y_u, z_u]^T\) and \([x^p, y^p, z^p]^T\) are the coordinates of the receiver and the satellite respectively, \(c\) is the speed of light, \(\delta t_u\) is the receiver clock error and \(e_u^p\) is the measurement error. In SPP, \(n_s\) satellites \((n_s \geq 4)\) are observed, and the user position \([x_u, y_u, z_u]^T\) and the receiver clock error \(c\delta t_u\) is estimated by the nonlinear weighted least squares method. In order to give the weight of the measurement, in this paper, we assume the measurement noise \(e_u^p\) is the Gaussian white noise with zero mean and variance \(\sigma_p^2 = 0.09[m^2]\).

Table 2 shows the experimental condition. We have conducted experiments with the following three methods:

(i) All the received satellites are used for the position calculation.

(ii) The NLOS satellites are excluded from the position calculation.

(iii) The variance of each measurement is weighted depending on the NLOS satellite’s elevation angle \(\theta\) as follows:

\[
\tilde{\sigma}_p^2 = \frac{1}{\sin^2 \theta} \sigma_p^2
\]

We collected the receiver data of 300 epochs at 1 second interval with the fixed receiver FLEX6 and GPS-703 antenna made by NovAtel. Fig. 8 shows the experiment location and antenna position. The experiment was conducted on the road nearby a high-rise building in Kusatsu City, Japan.
Table 2: Experimental Condition (Positioning)

| Date          | September 28, 2019 |
|---------------|---------------------|
| GPS-Time      | 03:10:10 ~ 03:14:59 |
| Location      | Kusatsu City        |
| Receiver      | FLEX6-TAQ-B0G-TTN (NovAtel) |
| Antenna       | GPS-703-GGG (NovAtel) |
| Epoch interval| 1 [s]               |
| Elevation mask| 10 [deg]            |
| Measurement Data | C/A code          |
| Used Satellites | GPS, GALILEO, QZSS |
| Positioning method | single frequency point positioning |
| Estimation method | Least squares method |

Fig. 8: Experiment Location

Fig. 9: Inference Result (Antenna-Position)

Fig. 9 shows the inference result of the image taken at antenna position. It can be seen that we can infer the sky area with high accuracy.

Since the satellite constellation calculated from the elevation angle and the azimuth angle have characteristic of an equidistant projection, it is transformed into an orthogonal projection as described in Section 3.2. We inverted the image horizontally in order to match east and west because we took the image in the zenith direction. As a result, the satellite plotted in the obstacle area is estimated as an NLOS satellite. Fig. 10 shows the plots of satellite constellation before and after the projective transformation. It can be seen that G2, G7, G17, G19, G23, E13 and J3 satellites are plotted in the obstacle area.

The minimum number of satellites for position calculation is theoretically four. However, the position obtained from four satellites sometimes includes large error. Therefore, in this experiment, when the NLOS satellite is excluded, we excluded the NLOS satellites in ascending order of their elevation angles as we can use at least 6 satellites in the position calculation. For example, if there are 4 LOS and 4 NLOS satellites, then we use 6 satellites of 4 LOS and 2 NLOS with higher elevations.

Fig. 11, Fig. 12 and Fig. 13 show the positioning results plotted on Google Maps.

Fig. 10: Projective Transformation

Fig. 11: Positioning Result (Method (i))
The yellow pin is the position obtained by the PPP (Precise Point Positioning) method [9] with applying CLAS (Centimeter Level Augmentation Service) data from Japan QZSS (Quasi-Zenith-Satellite-System) [10] and it is assumed to be true position in evaluating the positioning results in this experiment. The PPP is a method that receives code and carrier phase from a satellite with a single receiver and estimates receiver position. This technology can be accomplished with centimeter level error [11].

From this result, it can be observed that the coordinates which were scattered by the method (i) and the method (ii) are gathered around the provisional true value by the method (iii). The results of the method (ii) sometimes scattered in the northeast area. It is considered that the satellite positions are gathered in the northeast direction by excluding NLOS satellites. Fig. 14, 15 and 16 show the ENU error and satellites visibility with each method.
Table 3: Positioning Error

| Method                  | Direction | RMS [m] | 3DRMS [m] |
|-------------------------|-----------|---------|-----------|
| (i) (All Satellites)    | East      | 4.61    | 6.98      |
|                         | North     | 8.76    |           |
|                         | Upper     | 6.93    |           |
| (ii) (Excluded NLOS)    | East      | 12.52   | 18.9      |
|                         | North     | 12.92   |           |
|                         | Upper     | 27.39   |           |
| (iii) (De-weighted NLOS)| East      | 4.46    | 4.50      |
|                         | North     | 4.46    |           |
|                         | Upper     | 4.56    |           |

Table 3 shows the statistics of positioning error. From these results, it can be considered that the positioning accuracy in North, East and Upper direction is improved by de-weighting NLOS satellites. Because, we consider that the pseudo-range data from the NLOS satellites contain large multipath errors. The method (ii) has been not improved by compared to the method (i) in positioning accuracy, because the number of satellites decreased by excluding the NLOS satellites. Fig.16 shows that number of used satellites sometimes decreased to 6. From the above, we can say that the method (iii) can perform better positioning accuracy in SPP(Single Point Positioning).

5 Conclusion

In this paper, we have developed the method can continue to provide accurate position information by not only excluding NLOS satellites but also method to de-weight them. The fcn used in the sky area segmentation made it possible to infer highly accurate. It is expected that more accurate inference can be performed by increasing learning data. In addition, we could improve the positioning accuracy by de-weighting NLOS satellites in SPP. Since there is a problem that the method is examined at just one point in actual GNSS positioning circumstances. We will conduct experiments of segmentation of the sky image as well as the GNSS positioning circumstance in the future study.

References

[1] K. Horide, A. Yoshida, R. Hirata, Y. Kubo and Y. Koya: NLOS Satellite Detection Using Fish-Eye Camera and Semantic Segmentation for improving GNSS Positioning Accuracy in Urban Area, Proceedings of the 50th ISCIE International Symposium on Stochastic Systems Theory and Its Applications, Kyoto, Nov. 1-2, pp. 212–217, 2018.
[2] M. Petovello: Multipath vs. NLOS signals, Inside GNSS, 2013 November/December, pp. 40–44, 2013.
[3] J. Long, E. Shelhamer and Trevor Darrell: Fully Convolution Networks for Semantic Segmentation, Proceedings of Computer Vision and Pattern Recognition (CVPR) 2015, pp. 3431–3440, Boston, 2015.
[4] T. Harada, Image Recognition, Koudansya, 2017 (in Japanese).
[5] K. Simonyan and A. Zisserman: Very Deep Convolutional Networks for Large-Scale Image Recognition, CoRR, abs/1409.1556, 2014 (from: http://arxiv.org/abs/1409.1556).
[6] Visual Object Classes Challenge 2012 (VOC2012) (from: http://host.robots.ox.ac.uk/pascal/VOC/voc2012/).
[7] Y. Kubo: (Appendix 3) Positioning Algorithms for the Point Positioning, in GPS Handbook, ed. by S. Sugimoto and R. Shibasaki, pp. 422–431, Asakura, 2010 (in Japanese).
[8] B. W. Parkinson and J. J. Spilker Jr. (Eds.): Global Positioning System: Theory and Applications, Vol. I, II, AIAA, Washington, DC, 1997.
[9] S. Sugimoto and Y. Kubo: GNSS Regressive Models and Precise Point Positioning, Proc. 36th ISCIE International Symposium on Stochastic Systems Theory and its Applications, pp. 159–164, Saitama, Oct., 2004.
[10] N. Motooka, Hirokawa, K. Nakakuki, S. Fujita, M. Miya and Y. Sato, CLASLIB: An open-source toolkit for low-cost high-precision PPP-RTK positioning, Proc. ION GNSS+ 2019, pp. 3695–3707, Miami, Florida, Sep., 2019.
[11] Cabinet Office: Quasi-Zenith Satellite System Performance Standard (PS-QZSS-001), Nov., 2018 (available from: https://qzss.go.jp/en/technical/ps-is-qzss/ps-is-qzss.html).