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Azimuth estimation based on CNN and LSTM for geomagnetic and inertial sensors data

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Abstract

Although estimating the azimuth using a geomagnetic sensor is very useful, the estimation error may be very large due to the surrounding geomagnetic disturbance. We proposed a novel method for preprocessing appropriately for geomagnetic and inertial sensor data to be suitable for the proposed Artificial Neural Network model and training method for the model. As a result, the probability of azimuth estimation error within 1 degree is 96.4% with regression estimation. For classification estimation, when the azimuth estimation probability is 90% or more, the probability that the azimuth estimation error is within 1 degree is 100%.

Keywords: Azimuth; Geomagnetic sensor; Inertial sensor; LSTM; Sensor fusion

1. Introduction

Estimating an azimuth using a geomagnetic sensor has long been very important in human life. However, there is a problem in that a large error occurs in the estimated azimuth because the earth's magnetic field is distorted by the influence of the surroundings indoors or outdoors with steel structures around it [1]. Therefore, various studies have been conducted to solve this problem.

When the geomagnetic sensor values measured in the X-Y-Z direction are M_x, M_y, and M_z, respectively, while rotating the geomagnetic sensor horizontally at an arbitrary place, the estimated azimuth is calculated by equation $-tan^{-1}$ (M_y/M_x). If there is no geomagnetic disturbance, when M_x and M_y are drawn on the two-dimensional plane of X-Y, they become concentric circles centered on the origin. However, if there is a geomagnetic disturbance caused by a nearby metal material, the center point of the circle moves away from the origin, and the circle also becomes an ellipsoid or distorted shape rather than a concentric circle. The simplest calibration method is hard iron calibration, which moves the center point to the origin, based on the maximum and minimum values of the X and Y axes of the measured data, respectively. In addition, soft iron correction is performed by calculating the distance between the major axis and the minor axis of the ellipse, calculating the angle of rotation in the X-Y axis of the ellipse axis, and converting it into a form close to a circle.

If the azimuth angle is calculated after forcibly fitting the measured geomagnetic sensor data in the form of concentric circles, the accuracy is slightly improved. However, the estimated azimuth has an error of even several tens of degrees depending on the geomagnetic measurement location even in the same building, so there is a limit to its use for precise azimuth measurement [2,3]. To improve the accuracy, the least square algorithm and the inertial sensors to estimate the gravity direction were used to estimate irregular circular models [4,5]. There is also a research result that greatly reduced the azimuth estimation error to ±2 degrees by installing 12 geomagnetic sensors on two vertical plates and calibrating the measurement data to a 3D sphere manifold, but geomagnetic sensors were used too much [6]. Also, in [7], the maximum likelihood algorithm was used to fit the measurement data to a 3D ellipsoid, and finally, the range of fluctuation of the compensated sensor reading was greatly reduced. However, even if the geomagnetic sensor measurement data is concentrically fitted, the azimuth estimation error is not small. Since geomagnetic sensor measurement values have very different error patterns depending on geomagnetic disturbance, there is a fundamental limitation in the calibration method of geometric data. In [8],

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a method of correcting the geomagnetic error while rotating in the direction of several axes using a geomagnetic sensor, and an acceleration sensor that measures the direction of gravity was proposed, and azimuth error of about 1 degree to 2 degrees was obtained. However, performance verification has not been confirmed because it has not been tested in various places.

Also, in [9], the geomagnetic sensor and inertial sensor data were measured while rotating in place at an arbitrary point. And after calibrating the hard iron and soft iron of the geomagnetic sensor data, the geomagnetic sensor data was sampled at every rotation angle of 10 degrees. A method of probabilistically analyzing the difference with concentric circles of this data has been proposed to determine the accuracy of the measured geomagnetic azimuth at the corresponding point. But this is not for estimating the azimuthal angle using the data.

Meanwhile, there have been attempts to apply Artificial Neural Network (ANN) technology to predict geomagnetic disturbance models using solar wind data [10]. In [11], three-layer neural networks with 12 neurons in a hidden layer were trained with geomagnetic sensor measurement data and true azimuth, and the average azimuth estimation error was about 2 degrees, and the Root Mean Square (RMS) value was 6.3 degrees. Ref. [12] determined the accuracy of measured geomagnetic sensor data using a Recurrent Neural Network (RNN) based on Long Short-Term Memory (LSTM). Ref. [13] estimated the label with an unsupervised method and applied a 1-dimensional Convolutional Neural Network (CNN) to determine the accuracy of the geomagnetic sensor data measured while moving. And the performance was improved compared to the case of using the Kalman filter.

In [14], the simple LSTM with 4 hidden layers was proposed to estimate the azimuthal angle using equally sampled geomagnetic sensor data. However, the number of training data and test data were not enough, and the estimation error is not small from 0.25 degree to 2.23 degree.

Meanwhile, an ANN model combining CNN to efficiently extract features from the stock price data and LSTM to predict the future value showed good performance, especially for the times series data [15]. CNN-LSTM based on continuous blood pressure monitoring was tried to estimate blood pressure [16]. However, according to [17] for power quality disturbance detection, the performance of CNN, LSTM, CNN-LSTM, and preprocessed CNN-LSTM is similar. Therefore, to increase estimation performance, appropriate selection of the ANN model, understanding of data properties, preprocessing of training data, and training method are very important.

In this paper, we have developed a novel method to apply ANNs for estimating azimuthal angles using geomagnetic and inertial sensor data. The best ANN model from the various combinations of CNN, RNN, and LSTM and data preprocessing methods were established to maximize the estimation accuracy through many experiments and training processes. It includes a training data sampling method with an equal rotation interval of 1 degree and generating the training data with rotating data elements. In addition, after many attempts, it was discovered that the azimuth estimation error varies greatly depending on the format of expressing repeated azimuth angles based on 360 degrees.

Geomagnetic sensor data was measured at a total of 181 locations, and tested with data from 62 locations not used in training, resulting in very accurate results of an average estimated azimuth error of 0.27 degrees and an RMS error of 0.37 degrees by regression estimation.

2. Measurement of geomagnetic and inertial sensor data

In this paper, we do not use expensive precise measuring instruments to measure geomagnetic sensor data, but rather that people can easily measure them in any place using low-cost devices such as smartphones. This is because these assumptions are realistic and practically applicable. In particular, to train ANNs, geomagnetic sensor data measured in a wide variety of places is required, but it is difficult to obtain a large amount of sensor data if the measurement device is special and the measurement method is difficult.

A common device such as a smartphone has a built-in geomagnetic sensor, an accelerometer sensor, and a gyro sensor. The user can measure the M_x, M_y, and M_z geomagnetism values by constant time intervals in the X-Y-Z axes, respectively, using the geomagnetic sensor while holding the smartphone and rotating it in place. However, since the user is not a mechanical device and cannot rotate at a constant rotational speed, the geomagnetic value cannot be measured at regular intervals of the measurement azimuth while rotating once. While the user pauses while rotating, many geomagnetic sensor values are measured at the corresponding azimuth. To train a neural network, it is difficult to obtain good results if the training data is biased to a specific value. Therefore, it is important to measure geomagnetic sensor values at regular intervals in the 360-degree rotation direction.

To this end, while the user rotates in place, the value of the acceleration sensor and gyro sensor built into the smartphone are simultaneously collected along with the value of the geomagnetic sensor. By applying the accelerometer and gyro sensor values to EKF, the yaw rotation angle φ can be estimated [9,14,18].

The points in Fig. 1 represent the measured and uncalibrated geomagnetic sensor values M_x and M_y on the 2D X-Y plane while the user rotates in place at an arbitrary place. Since the user cannot rotate at a constant speed, the density of dots is not constant. In addition, hard iron geomagnetic disturbance in which the center of the trajectory of the points deviates from the origin of the X-Y plane and soft iron disturbance in which the trajectory is distorted and deviates from the concentric circle can be confirmed. In Fig. 1, the x marks are geomagnetic sensor data sampled at every 10-degree rotation angle using an inertial sensor and EKF when the geomagnetic sensor rotates at an irregular speed. The reason why the x spacing looks uneven is that the measured data of M_x and M_y are inaccurate due to the magnetic disturbance. In other words, if the ANN is trained using geomagnetic sensor data measured at irregular rotational speeds, more data is trained for a specific azimuth, reducing estimation accuracy. In addition, if the azimuth calculated by formula $-tan^{-1}(M_y/M_x)$ for the measured geomagnetic data is used as a label, a label that is not true is used, so training does not work properly.

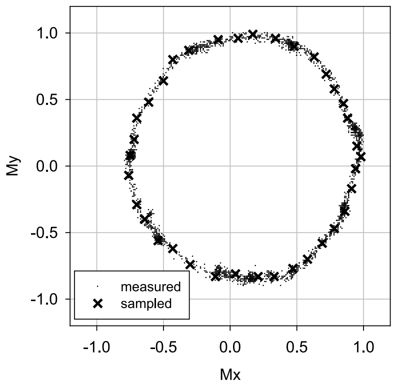


Fig. 1. The points are the measured and uncalibrated geomagnetic sensor data while the user rotates irregular speed in place. And the x marks are geomagnetic sensor data sampled at every 10-degree rotation angle.

The yaw rotation angle estimated using the inertial sensor and EKF is relatively accurate. Therefore, when measuring geomagnetic sensor data, if the initial azimuth is accurately measured with a separate measuring instrument, other azimuths during 360-degree rotation can be accurately estimated using this. Therefore, the azimuth estimated at regular intervals using this is used as a label when training the supervised neural network. In addition, equal intervals can be adjusted to any size, and as confirmed later, the size of equal intervals is related to the accuracy of azimuth estimation using neural networks.

3. Training methods for artificial neural network

To train ANNs to have high-performance estimation ability, it is very important to preprocess training data as suitable for estimation purposes [19]. Therefore, the data from the geomagnetic sensor whose rotation angle was non-uniformly measured in Section 2 was calibrated with data sampled at each uniform rotation angle.

In addition, due to the nature of geomagnetic sensor data, if it rotates in place and is continuously measured, it has unique pattern properties of M_x and M_y on the 2D X-Y plane. This pattern varies from place to place but is independent of the azimuth at which the measurements are initially taken. In addition, by using an inertial sensor and EKF that relatively accurately estimate a rotation angle, the azimuth at an arbitrary rotation angle can be accurately calculated by adding the rotation angle to the initial azimuth.

Considering the characteristics of these geomagnetic sensor data, and the relationship between inertial sensor data and geomagnetic sensor data, the ANN was trained in the following way.

That is, the geomagnetic sensor data for training the ANN was sampled at each rotation angle of 1 degree, so a total of 360 geomagnetic sensor data was measured in one place. At this time, the azimuth angle at which the measurement starts is always based on the north, that is, the azimuth angle is 0 degrees. When the ANN is trained by regression to estimate the real-valued azimuth angle, there are a total of 360 input nodes in the neural network, and the measured 360 geomagnetic sensor data corresponds to each input node. At this time, the label is north or 0 degrees. The data input to each input node is M_x, M_y, M_z and the measured azimuth, calculated with M_x and M_y, as in Fig. 2.

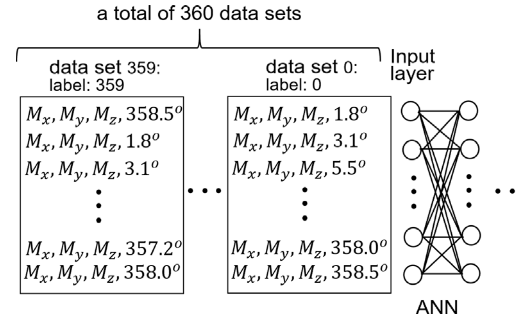


Fig. 2. The total 360 training data sequences are generated based on the data set 0 by rotating the data elements 1 degree each.

However, in the later test stage, since the azimuth angle at which the measurement starts is an arbitrary angle in units of 1 degree, various measurement start angles must be learned. Therefore, as shown in Fig. 2, we create data set 0 whose measurement start angle is north, i.e., label 0, and each data set whose data is rotated by 1 degree based on this data set 0. The label means the true azimuth. Finally, data set 359 with label 359 is created, and data sets from 0 to 359 are sequentially input to the input layer to train the ANN.

In this paper, LSTM specialized for the continuity of learning data was mainly used, to train the ANN by utilizing the characteristics of the patterns of M_x, M_y, M_z, and calculated azimuth angle, measured continuously while rotating the geomagnetic sensor in place [20].

As a result of the training and testing of various ANN models, it was found that the azimuth estimation performance of the 4-layer CNN and LSTM model was the best.

4. Experiments

Using smartphones Samsung Galaxy Note 5 and S10, data from the geomagnetic sensor, accelerometer sensor, and gyro sensor were measured in the X, Y, and Z axes, respectively, at 10 msec time intervals starting from the north direction. For all geomagnetic sensor data measurements, rotation angles were estimated by applying inertial sensor data and EKF, and geomagnetic sensor data was sampled every time the rotation angle increased by 1 degree. That is, 360 pieces of M_x, M_y, M_z data, and the calculated azimuth become the basic training data set, and the label at this time becomes 0 degrees or north. In addition, according to the label azimuth rotated by 1 degree, the M_x, M_y, M_z data, and the calculated azimuth angle are also rotated to become another learning data set. Since there are 360 rotations in all, the ANN is trained with a total of 360 data set sequences for one location as in Fig. 2.

Sensor data was measured at 181 locations in a total of five buildings. Data from 119 locations were used to train the ANN, and data from separated 62 locations were used for testing. A total of 360 training data sets and labels are created by rotating the data in a circular shift method by 1 degree for each data in one place. Therefore, a total of 42,840 data sets were used for training, and the azimuth was estimated for 22,320 test data sets.

The data set used in the test is the same as the format of the dataset used in training, as shown in Fig. 2. M_x, M_y, M_z data, and the calculated azimuth are input to 360 input nodes of the input layer. However, only one random data set among 360 data sets is entered and the corresponding label is used as a true azimuth. Therefore, 360 test data sets of different azimuths can be created and tested at one test location. At the output node of the output layer, the estimated azimuth in real value format is output.

Firstly, the azimuth was estimated using only LSTM, but the performance was poor, so learning was attempted by combining CNN and LSTM. According to the attribute of CNN to extract features from the consecutive geomagnetic data and the attribute of LSTM to predict the value for the times series data, the combined CNN and LSTM could show better performance. Fig. 3(a) shows the azimuth estimation performance for various ANN methods and conventional methods fitting the measured geomagnetic sensor data in the form of concentric circles. The model that connects 4 CNN layers and LSTM shows better performance than the model using only LSTM. It can be seen that the cumulative probability of the azimuth estimation error is 96.4% within 1 degree and 99% at 1.85 degrees. Also, for 90% of all test data, the azimuth estimation error is within 0.7 degrees. The performance is much better than when using CNN with 4 layers or RNN. CNN4+LSTM_1 is the result of training by rotating the learning data in units of 1 degree, and CNN4+LSTM_10 is training by rotating it in units of 10 degrees. Since the rotation method by 1 degree has much better performance, it can be confirmed that the training data preprocessing method we proposed is appropriate.

(b) is the estimation performance according to the number of different CNN layers, and CNN4+LSTM has the best performance. (c) is the azimuth estimation result of the CNN4+LSTM method for the five measured buildings. Accuracy is different for each measurement data of buildings, but except for "Wu", which has a large influence on geomagnetic disturbance due to its steel structure, most of the estimation errors are within 1 degree, and the consistency of the estimation performance can be confirmed.

(d) is a performance analysis according to whether or not M_z data is included and how to mark the calculated azimuth when training the ANN. Considering the azimuth estimation error performance, M_z data is not used to calculate the azimuth, but it is better to include it as in CNN4+LSTM_XYZ in the training data for ANN learning. In addition, the azimuth calculated as $-tan^{-1}(M_y/M_x)$ included in the training data goes around based on 360 degrees due to the nature of the azimuth. However, it was confirmed that the azimuth estimation performance is much better when monotonically increased to allow the azimuth to be marked more than 360 degrees as in CNN4+LSTM_XYZ_mono, rather than folded to less than 360 degrees.

Fig. 4(a) is part of the code for programming the ANN model of CNN4+LSTM with TensorFlow [21], which shows

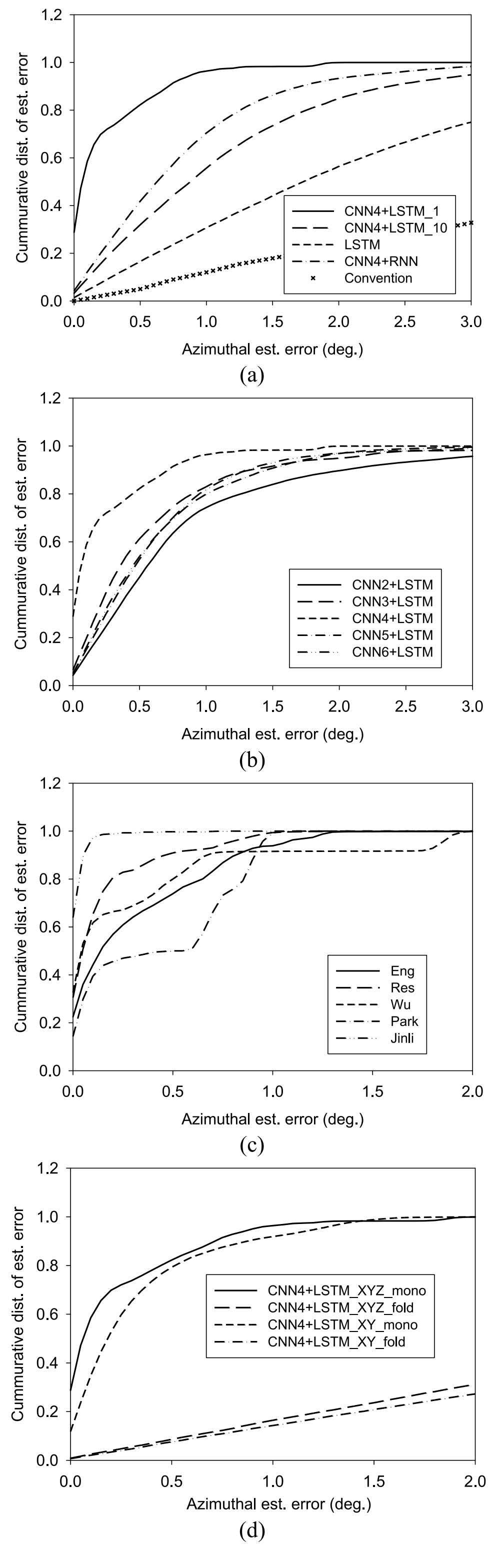
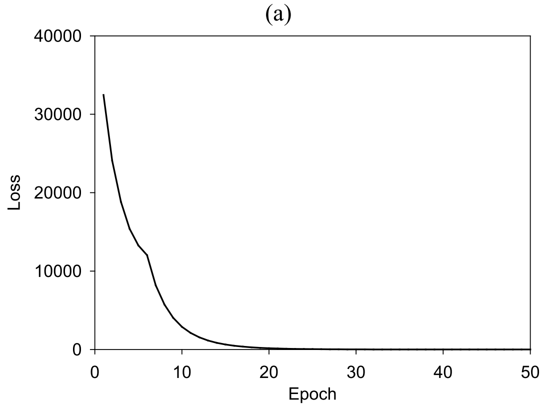


Fig. 3. Accumulated azimuth estimation error probability according to various ANN models, sensor data measurement locations, and mark method of calculated azimuth. (a) the azimuthal estimation performance for various ANN methods and conventional methods, (b) the estimation performance according to the number of different CNN layers, (c) the azimuthal estimation result of the CNN4+LSTM method for the five measured buildings, and (d) the performance analysis according to whether or not data is included and how to mark the calculated azimuth when training the ANN.

```
model = Sequential()
model.add(Conv1D(filters=32, kernel_size = 3, activation = 'relu'))
model.add(Conv1D(filters=32, kernel_size = 3, activation = 'relu'))
model.add(MaxPooling1D(pool_size = 3, strides = 2))
model.add(Conv1D(filters=64, kernel_size = 3, activation = 'relu'))
model.add(Conv1D(filters=64, kernel_size = 3, activation = 'relu'))
model.add(MaxPooling1D(pool_size = 3, strides = 2))
model.add(LSTM(360, activation = 'tanh'))
model.add(Dense(1, activation = 'relu'))
model.build(input_shape = X.shape)
model.summary()
opt = tf.optimizers.Adam(learning_rate=0.0007)
model.compile(optimizer = opt, loss = 'mse', metrics = ['mae'])
history = model.fit(X_train, y_train, epochs = 2000, batch_size = 256,
validation_split = 0.2, callbacks = [checkpoint_cb, early_stopping_cb])
pred = model.predict(X_test)
model.evaluate(X_test, y_test)
```

(a)



(b)

Fig. 4. A TensorFlow code for the CNN4+LSTM model and the learning curve. (a) the TensorFlow code for the CNN4+LSTM model, and (b) the learning curve for the model.

the detailed ANN model description, and (b) is the learning curve of it. The kernel size of the CNN is 3, 32 feature maps are generated, and "relu" is used as the activation function. In addition, max pooling with a stride of 2 and a pool size of 3 was used between CNNs. In the LSTM layer, tanh was used as an activation function, and in the output layer, "relu" was used as an activation function. Since the training data set is large, batch learning was performed with 256 data at a time, and it converged at about 300 epochs.

On the other hand, CNN4+LSTM was trained by classification estimation using the geomagnetic sensor and the calculated azimuth data. In this case, the output layer consists of 360 output nodes meaning estimated azimuth, respectively, and the previous layer uses a softmax layer to estimate accuracy probabilities corresponding to output nodes from 0 degrees to 359 degrees. Among the probabilities output from 360 output nodes, the node corresponding to the largest value is selected as the estimated azimuth. Training data, labels, test data, and learning methods are the same as those of regression estimation.

Table 1 is the result of estimating the azimuth in units of 1 degree by classification estimation. Accuracy probability is the probability of the output node of the output layer. And hit

Table 1
Azimuth estimation error probability in classification estimation.

Accuracy probability	Hit ratio	Azimuth estimation error angle [deg.]	True ratio for the hit case with the est. error
0.98	0.61	0	0.89
		1	0.11
0.96	0.80	0	0.88
		1	0.12
0.94	0.87	0	0.87
		1	0.13
0.92	0.89	0	0.87
		1	0.13
0.90	0.90	0	0.86
		1	0.14

ratio is the proportion of test data sets with a node, whose probability is greater than the accuracy probability among the 360 output nodes, for 22,320 test data sets. The true ratio is the ratio of the test data set to the estimated azimuth error for 22,320 test data sets when there is an output node greater than the accuracy probability.

The case of generating an accuracy probability of 98% or more among 360 output nodes for a test data set is 61% for the entire 22,320 test data sets. In this case, the case where the estimated azimuth error is 0 degrees is 89%, and the case where the estimated azimuth error is 1 degree is 11%. No errors greater than 2 degrees occurred. In addition, 90% of the test data sets estimated the node with an accuracy of 90% or more. And in this case, the estimated azimuth error is 86% for 0 degrees and 14% for 1 degree, so the difference from the 98% case is not large.

As a result, when the azimuth is estimated with an accuracy of 90% or more among the output node values for a test data set, the probability that the azimuth is true is 86% or more, and the probability of an error within 1 degree is 100%. In other words, when the neural network model is trained by the method proposed in this paper, in the case of classification estimation, the azimuth estimation error shows very good performance that is within 1 degree. Fig. 5 shows an enlarged part view of CNN4+LSTM estimation results for any three test places, and the estimated azimuthal angles match well with true angles.

5. Conclusion

In this paper, we proposed a novel method to apply ANNs for estimating azimuthal angles using geomagnetic and inertial sensor data measured rotating in one place. The best ANN model of four CNN layers and an LSTM layer was developed, and a training data sampling method with an equal rotation interval, generating the training data with rotating data elements, and the format of expressing repeated azimuth angles were verified. It shows much better performance compared to the conventional method.

As future research, it is necessary to collect and learn sensor data from more diverse types of places, and to estimate instantaneous geomagnetic azimuth while moving without rotating in place.

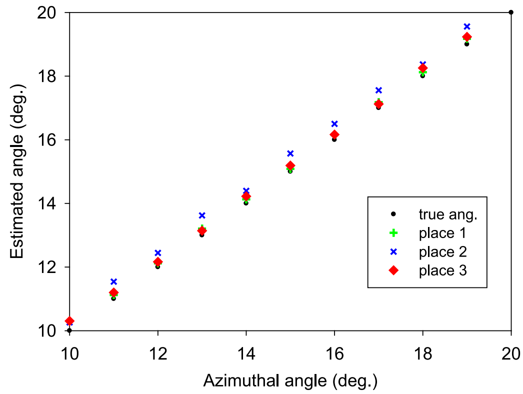


Fig. 5. Enlarged part view of CNN4+LSTM estimation results for three test places.

Declaration of competing interest

The authors declare that there is no conflict of interest in this paper.

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