

DESCRIPTION

Title of Invention

PREDICTION MODEL CREATION DEVICE, PREDICTION MODEL
CREATION METHOD, AND PROGRAM

[Technical Field]

[0001]

The present invention relates to a prediction model creation device, a prediction model creation method, and a program for predicting a positioning error distribution.

[Background Art]

[0002]

When a satellite positioning system such as a GNSS is utilized, position information and positioning error information indicating the size of an error of the position information can be obtained. Patent Document 1 describes a technique for calculating a positioning error based on errors between pseudo distances from a plurality of satellites and distances from a measured position to the satellites.

[0003]

The description will be given with reference to Fig. 8. Regarding a vehicle traveling on a road A shown in Fig. 8, when a traveling position of the own vehicle is

measured by a satellite positioning system, there is a possibility that the result that the vehicle travels on a nearby road B instead of the road A can be obtained depending on the degree of error in the measured position information. In the case of charging according to the road on which the vehicle travels, misrecognition of the road on which the vehicle travels becomes a problem. A technique is provided to prepare the misrecognition of roads such that a probability of making a mistake on the road on which the vehicle travels (hereinafter referred to as a failure rate) is calculated by utilizing the positioning error information provided by the satellite positioning system.

[0004]

Both L1 and L2 in Fig. 8 indicate a distribution of positioning errors. The positioning errors are normally distributed, and a standard deviation of the normal distribution is defined as the "positioning error". The distribution L1 indicates a probability distribution when the positioning error thereof is smaller than that of the distribution L2. The description will be given with reference to Fig. 9. The vertical shaft of a graph in Fig. 9 indicates the failure rate, and the horizontal shaft indicates the size of the positioning error. In Fig. 9, a difference D1 between a positioning error R1 and a

positioning error R2 and a difference D2 between the positioning error R2 and a positioning error R3 are equal to each other. However, a difference D3 between a failure rate when it is the positioning error R1 and a failure rate when it is the positioning error R2 is significantly different from a difference D4 between a failure rate when it is the positioning error R2 and a failure rate when it is the positioning error R3. That is, the size of the positioning error is not proportional to the failure rate. Therefore, when handling the failure rate, the difference D1 between the positioning error R1 and the positioning error R2 and the difference D2 between the positioning error R2 and the positioning error R3 should not be treated as equivalent.

[Citation List]

[Patent Document]

[0005]

[Patent Document 1] Japanese Unexamined Patent Application Publication No. 2019-15635

[Summary of Invention]

[Technical Subject]

[0006]

Generally, when creating a prediction model, learning is performed so as to minimize or maximize a predetermined evaluation function. For example, when the

prediction model is created by using the least squares error as the evaluation function and reducing the error between the predicted value and the measured value of the positioning error, there is also a possibility of creating the prediction model for predicting the positioning error R3 when the size of the true positioning error is R2, and there is also a possibility of creating the prediction model for predicting the positioning error R1 when the true size of the positioning error is R2, and then it is conceivable that values of the evaluation functions are the same in both cases. Therefore, this prediction model may become a model in which the failure rate of misrecognition of the road A and road B is significantly different from the actual failure rate. With such a prediction model, it is not possible to ascertain the accurate failure rate.

[0007]

The present disclosure provides a prediction model creation device, a prediction model creation method, and a program capable of solving the above-mentioned subjects.

[Subject to be solved]

[0008]

An aspect of the present invention, there is provided a prediction model creation device that creates a prediction model for predicting a positioning error

indicating an error in a position measured by a satellite positioning system, the prediction model creation device includes: a data acquisition unit that acquires topographical feature data indicating a topographical feature of a certain location, the positioning errors with respect to positions of a moving body observed by the satellite positioning system when the moving body passes the location a plurality of times, and the number of times of observation for each of the positioning errors; a prediction model creation unit that creates a prediction model for outputting a probability distribution of the positioning errors when the topographical feature data is input; an evaluation unit that calculates an evaluated value of a failure rate, which is calculated based on a predetermined function and the probability distribution of the positioning errors output by the prediction model and indicates a degree of possibility of occurrence of misrecognition with respect to the positions, based on an observation failure rate calculated based on the function and the number of times of observation for each of the positioning errors; and an update unit that updates the prediction model such that the evaluated value becomes an optimal value.

[0009]

Another aspect of the present invention, there is

provided a prediction model creation method for creating a prediction model for predicting a positioning error indicating an error in a position measured by a satellite positioning system, the prediction model creation method includes: an acquisition step of acquiring topographical feature data indicating a topographical feature of a certain location, the positioning errors with respect to positions of a moving body observed by the satellite positioning system when the moving body passes the location a plurality of times, and the number of times of observation for each of the positioning errors; and a creation step of creating a prediction model for outputting a probability distribution of the positioning errors when the topographical feature data is input, in which in the creation step of creating the prediction model, an evaluated value of a failure rate, which is calculated based on a predetermined function and the probability distribution of the positioning errors output by the prediction model and indicates a degree of possibility of occurrence of misrecognition with respect to the positions, is calculated based on an observation failure rate calculated based on the function and the number of times of observation for each of the positioning errors, and the prediction model is updated such that the evaluated value becomes an optimal value.

[0010]

Still another aspect of the present invention, there is provided a program for causing a computer to execute a process of a prediction model creation method for creating a prediction model for predicting a positioning error indicating an error in a position measured by a satellite positioning system, the process includes: an acquisition step of acquiring topographical feature data indicating a topographical feature of a certain location, the positioning errors with respect to positions of a moving body observed by the satellite positioning system when the moving body passes the location a plurality of times, and the number of times of observation for each of the positioning errors; and a creation step of creating a prediction model for outputting a probability distribution of the positioning errors when the topographical feature data is input, in which in the creation step of creating the prediction model, an evaluated value of a failure rate, which is calculated based on a predetermined function and the probability distribution of the positioning errors output by the prediction model and indicates a degree of possibility of occurrence of misrecognition with respect to the positions, is calculated based on an observation failure rate calculated based on the function and the number of times of observation for each of the positioning

errors, and the prediction model is updated such that the evaluated value becomes an optimal value.

[Advantageous Effects of Invention]

[0011]

According to the above-mentioned prediction model creation device, the prediction model creation method, and the program, it is possible to create a prediction model for estimating a distribution of errors in positions measured from positioning utilizing a satellite.

[Brief Description of Drawings]

[0012]

Fig. 1 is a diagram showing an example of a prediction model creation device according to a first embodiment of the present disclosure.

Fig. 2 is a first diagram for describing a creation method of a prediction model of the present disclosure.

Fig. 3 is a second diagram for describing a creation method of the prediction model of the present disclosure.

Fig. 4 is a flowchart showing an example of a prediction model creation process of the present disclosure.

Fig. 5 is a diagram showing an example of a prediction model creation device according to a second embodiment of the present disclosure.

Fig. 6 is a diagram for describing an evaluation

method of a prediction model according to the second embodiment of the present disclosure.

Fig. 7 is a flowchart showing an example of an evaluation process of the prediction model according to the second embodiment of the present disclosure.

Fig. 8 is a first diagram for describing a positioning error and a failure rate.

Fig. 9 is a second diagram for describing the positioning error and the failure rate.

Fig. 10 is a diagram showing an example of a hardware configuration of the prediction model creation device according to each embodiment of the present invention.

[Description of Embodiments]

[0013]

<First Embodiment>

Hereinafter, a positioning error prediction method according to a first embodiment of the present invention will be described with reference to Figs. 1 to 4.

(Configuration)

Fig. 1 is a diagram showing an example of a prediction model creation device according to the first embodiment of the present invention. As shown in Fig. 1, the prediction model creation device 10 includes a data acquisition unit 11, a prediction model creation unit 12,

and a storage unit 13.

[0014]

The data acquisition unit 11 acquires learning data necessary for creating a prediction model M for predicting a probability distribution of positioning errors of a satellite positioning system at any location. For example, the learning data includes information such as, for each of a plurality of locations, topographical feature data indicating a topographical feature of the location, speed data when a vehicle travels at the location, the number of times of observation for each of the positioning errors when the vehicle travels the location a plurality of times, and the total number of travels (the total number of times of observation).

[0015]

The prediction model creation unit 12 creates the prediction model M for predicting the probability distribution of the positioning errors of the satellite positioning system such that an accurate failure rate can be calculated. For example, the prediction model M outputs information such as a probability " r_2 " that a positioning error = 2[m] is observed, a probability " r_3 " that a positioning error = 3[m] is observed, ..., a probability " r_{11} " that a positioning error = 11[m] is observed. The prediction model creation unit 12 includes

a predicted value calculation unit 121, an evaluation unit 122, and an update unit 123.

[0016]

The predicted value calculation unit 121 estimates a true distribution of the positioning errors. The predicted value calculation unit 121 calculates a predicted value of a failure rate based on the estimated positioning error distribution. As will be described later, the predicted value of the failure rate is calculated as the distribution.

The evaluation unit 122 performs evaluation by comparing the failure rate calculated based on the positioning errors predicted by the prediction model M with the failure rate calculated from the distribution of the observed positioning errors. In the present embodiment, the failure rate is used as an evaluation function (loss function) instead of the positioning errors.

The update unit 123 updates a parameter of the prediction model M based on the evaluation of the evaluation unit 122 with respect to the failure rate based on the prediction model M.

[0017]

The storage unit 13 stores the prediction model M or various data.

[0018]

(Regarding Positioning Error)

In positioning using the satellite positioning system, even when the positioning is performed a plurality of times at the same location, the positioning errors are not constant and variations occur in positioning errors. The positioning error indicates the size of the errors of the position information measured by the satellite positioning system and indicates that an error can occur in a range of a circle centered on the position information and having the positioning error as a radius, for example. In the present embodiment, the variation in positioning errors is represented by the probability distribution. For example, while traveling 100 times with the vehicle at a certain location Q, the position information and the positioning errors at the location Q are received from the satellite positioning system. For example, out of 100 times, when the positioning error 2[m] is observed 30 times, the positioning error 3[m] is observed 20 times, ..., the positioning error 11[m] is observed 1 time, the probability that the positioning error at the location P is 2[m] becomes 30%, the probability that the positioning error is 3[m] becomes 20%, ..., the probability that the positioning error is 11[m] becomes 1%. The prediction model M of the present embodiment outputs the probability distribution of the

positioning errors observed at the location Q when the topographical feature data of the location Q, the speed of the vehicle, and the like are input.

[0019]

(Calculation Method of Failure Rate)

The failure rate f is calculated by using the following equation (1).

$$f = f_2 \cdot r_2 + f_3 \cdot r_3 + \dots + f_{11} \cdot r_{11} \dots (1)$$

Wherein, f_k is the failure rate when the positioning error is $k[m]$, and r_k is the true probability that the positioning error becomes $k[m]$. The true probability is a value of $n_k \div N$ assumed when n_k is defined as the number of times of observation of the positioning error $k[m]$, the total number of times of observation is defined as N , and $N \rightarrow \infty$.

[0020]

(Estimation of Positioning Error Distribution)

Since r_k is generally unobservable, it is estimated from the values of n_k and N . When n_k ($k = 2, 3, \dots, 11$) and N are known, a posterior probability $p(r_2, r_3, \dots, r_{11} | n_2, n_3, \dots, n_{11})$, in which the true probability is r_k , follows the Dirichlet distribution. The posterior probability p is shown in the following equation (2).

[0021]

$$p(r_2, r_3, \dots, r_{11} | n_2, n_3, \dots, n_{11}) = \frac{\Gamma(\sum_{k=2}^{11} (n_k + 1))}{\prod_{k=2}^{11} (\Gamma(n_k + 1))} \cdot \prod_{k=2}^{11} (r_k^{n_k+1}) \quad \dots (2)$$

[0022]

(True Value of Failure Rate)

Since the posterior probability p follows the Dirichlet distribution, the failure rate also has a distribution, and the distribution can be calculated by using the following equation (3).

$$f = \int (f_2 \cdot r_2 + f_3 \cdot r_3 + \dots + f_{11} \cdot r_{11}) \times p(r_2, r_3, \dots, r_{11} | n_2, n_3, \dots, n_{11}) dr_2 dr_3 \dots dr_{11} \dots (3)$$

The predicted value calculation unit 121 calculates an estimated value of the true positioning error distribution by using the equation (2) and calculates an observed value of the failure rate by using the equation (3). Further, in the present embodiment, it is assumed that the true value of the failure rate is f that is calculated by using the equation (3), and the probability distribution of the positioning errors, which is predicted by the prediction model M , and the failure rate f_{pred} , which is calculated by using the equation (1), are evaluated based on the f that is calculated by using the equation (3).

In equation (2), the distribution of positioning errors is estimated by using the Dirichlet distribution,

but it may be calculated by using the product of the binomial distribution instead of the Dirichlet distribution.

[0023]

(Evaluation Function)

When it is assumed that the probability distribution of the positioning errors, which is predicted by the prediction model M, and the failure rate, which is calculated by using the equation (1), are f_{pred} , the evaluated value L of f_{pred} is defined as a cumulative probability of the posterior probability of the failure rate estimated by using the equation (3) from the observation result in the vicinity of the predicted value as shown in the following equation (4). Wherein, b in the equation (4) is an allowable error of the failure rate.

[0024]

$$L = \int_{f_{pred}-b}^{f_{pred}+b} f dr_2 dr_3 \cdots dr_{11} \quad \cdots (4)$$

[0025]

The update unit 123 adjusts the parameters of the prediction model M such that the evaluated value L in the equation (4) is maximized. A recurrent neural network (RNN) can be used for the prediction model M. The topographical feature data, the speed data, and the like are used as input variables for the prediction model M.

When maximizing the evaluated value L , the predicted value calculation unit 121 does not handle the probability as it is but generates a plurality of sets of r_k ($k = 2$ to 11) by generating random numbers according to the distribution of the posterior probability p by using the Markov chain Monte Carlo (MCMC) method or the like and calculates the distribution of the failure rate by using the generated r_k set. The update unit 123 performs adjustment of the parameter based on the distribution of the failure rate.

[0026]

Next, a creation method of the prediction model M will be described with reference to Figs. 2 and 3.

Figs. 2 and 3 are a first diagram and a second diagram for describing the creation method of the prediction model of the present disclosure, respectively. Fig. 2 is a diagram when the total number of times of observation is small, and Fig. 3 is a diagram when the total number of times of observation is large.

Fig. 2(a) is a graph showing a space of the number of times of observation of the positioning error. n_2 and n_3 indicate the number of times the positioning error 2[m] is observed and the number of times the positioning error 3[m] is observed, respectively. For the convenience of description, n_2 and n_3 of n_2 to n_{11} are taken out and shown in the figure. This also applies to the following. Fig.

2(b) is a graph showing a space of the positioning error distribution. r_2 and r_3 indicate the probability that the positioning error 2[m] is observed and the probability that the positioning error 3[m] is observed, respectively.

[0027]

A point X_{12} in Fig. 2(a) indicates that the number of times the positioning error 2[m] is observed is n_2 and the number of times the positioning error 3[m] is observed is n_3 . The distribution Y_{12} in Fig. 2(b) indicates the distribution of the true posterior probabilities of the positioning errors for the number of times of observation is a combination of the values of the points X_{12} . That is, the distribution Y_{12} indicates the Dirichlet distribution according to the equation (2) in the case of the point X_{12} . Since the total number of times of observation in Fig. 2 is small, the spread of the distribution Y_{12} is large as compared with that in the case of Fig. 3 described below. A point Z_{12} in Fig. 2(b) indicates the predicted value of the probability distribution (probability r_2, r_3) obtained by the prediction model M being trained when the number of times of observation is n_2 and n_3 . Although the predicted value Z_{12} is far from the center of the distribution Y_{12} , it is evaluated to be a certain degree of certainty because the number of times of observation is small and the spread of the posterior distribution is large.

[0028]

Fig. 2(c) shows a graph indicating the distribution W of the failure rate (observation failure rate) calculated from the posterior distribution of the positioning errors, and the failure rate f_{pred} based on the predicted value Z_{12} obtained by the prediction model M . The vertical shaft in Fig. 2(c) indicates the probability, and the horizontal shaft indicates the failure rate. The predicted value calculation unit 121 generates a large number of random numbers $(r_1, r_2, \dots, r_{11})$ following the Dirichlet distribution, that is, the positioning error distribution following the Dirichlet distribution, based on the true posterior distribution Y_{12} by using a method such as MCMC. The predicted value calculation unit 121 calculates the graph W indicating the distribution of the observation failure rates from the generated positioning error distribution and the equation (3). The evaluation unit 122 calculates the failure rate f_{pred} from the predicted value Z_{12} in Fig. 2(b) and the equation (1). The width b in Fig. 2(c) depends on the number of times of observation or indicates a predetermined allowable width, and corresponds to b in the equation (4). The size of the shaded region Lw indicates the evaluated value with respect to the correctness of the prediction and corresponds to L in the equation (4). The evaluation unit

122 performs the evaluation of the correctness of the predicted value Z_{12} depending on how much the distribution W of the observation failure rate gathers in the vicinity of the failure rate f_{pred} calculated from the predicted value Z_{12} . The update unit 123 learns the parameter (RNN network coefficient) of the prediction model M such that the region L_w , which is included in the width of b centered on the failure rate f_{pred} based on the predicted value Z_{12} among the regions formed by the graph W and the coordinate shaft of the failure rate, becomes large.

[0029]

Fig. 3(a) shows a space of the number of times of observation of the positioning error when the number of times of observation is large. n_2 and n_3 are the number of times the positioning errors 2[m] and 3[m] are observed, respectively, but the total number of times of observation is larger than in the case in Fig. (a). In this case, in the space of the positioning error distribution in Fig. 3(b), the spread of the positioning error distribution Y_{12} becomes small. This indicates that the positioning error distribution Y_{12} converges closer to the true distribution due to the increase in the number of times of observation. The point Z_{12} in Fig. 3(b) is a predicted value obtained by the prediction model M . As described with reference to Fig. 2(c), the predicted value calculation unit 121

calculates the distribution W of the observation failure rate shown in Fig. 3(c) by using the random numbers generated based on the positioning error distribution Y_{12} in Fig. 3(b) and the equation (3). The evaluation unit 122 calculates the failure rate f_{pred} shown in Fig. 3(c) by using the predicted value Z_{12} in Fig. 3(b) and the equation (1). As shown in Fig. 3(c), when the total number of times of observation is large, the width W_h of the distribution W of the observation failure rate becomes narrower as the spread of the positioning error distribution Y_{12} decreases. In the example in Fig. 3(c), since an expected value W_c of the distribution W and the failure rate f_{pred} based on the predicted value are separated from each other, and the failure rate f_{pred} is outside the width W_h of the distribution W , the size of the region L_w is smaller as compared with that in the case of Fig. 2(c). If the failure rate f_{pred} is close to the expected value W_c of the distribution W , the width W_h of the distribution W is included in the allowable width b , and the area of the region L_w (the evaluated value L in the equation (4)) becomes the maximum. The predicted value Z_{12} in such a state is a target predicted value, and the prediction model creation unit 12 creates the prediction model M for calculating such a predicted value. For example, when the prediction model M is created using

the positioning errors or the like, which is observed at a location Q1 and a location Q2 having different topographical features, as learning data, the number of times of observation at the location Q1 is small, and the number of times of observation at the location Q2 is large, the prediction model creation unit 12 allows the expected value W_c of the distribution W having the spread as illustrated in Fig. 2(c) and the failure rate f_{pred} to be separated by a certain degree when the topographical feature data of the location Q1 is input and creates the prediction model that outputs the predicted value such that the expected value W_c of the narrow distribution W as illustrated in Fig. 3(c) and the failure rate f_{pred} approach each other when the topographical feature data of the location Q2 is input.

[0030]

Next, a flow of the prediction model creation process will be described.

Fig. 4 is a flowchart showing an example of the prediction model creation process of the present disclosure.

First, the data acquisition unit 11 acquires learning data (step S11). For example, the data acquisition unit 11 acquires, for each of a plurality of locations, the topographical feature data of the location,

the speed of the vehicle, the size of the positioning errors observed when the vehicle passes the target location a plurality of times, the number of times of observation thereof, and the total number of times of observation. The topographical feature data is, for example, the number and height of buildings existing in each direction centered on the target location, a route (shape of the road) on which the vehicle travels, or the like. Both the topographical feature data and the speed of the vehicle are elements that affect the reception of signals from the satellite positioning system at the target location. The topographical feature data can be obtained by analyzing three-dimensional map data. The speed of the vehicle and the positioning error can be obtained by actually making the vehicle travel a plurality of time in the same direction at the same speed for the same target location, and by recording the speed at that time, the position information acquired from the satellite positioning system, and the positioning error information. In the present embodiment, the topographical feature data, the speed of the vehicle, the number of times of observation for each of the positioning errors, and the total number of times of observation are defined as one set of learning data. For example, in a case where the positioning error 2[m] is observed 5 times, the

positioning error 3[m] is observed 3 times, and the positioning error 4[m] is observed 2 times when the vehicle travels a certain location 10 times, the number of times of observation for each of the positioning errors is information indicating that "the positioning error 2[m] is 5 times, the positioning error 3[m] is 3 times, and the positioning error 4[m] is 2 times", and the total number of times of observation is 10 times. The data acquisition unit 11 acquires the learning data for the plurality of locations having various topographical features and records the acquired learning data in the storage unit 13.

[0031]

Next, the prediction model creation unit 12 selects a plurality of sets from the learning data recorded in the storage unit 13 (step S12). Next, the prediction model creation unit 12 acquires the topographical feature data and the speed of the vehicle for each of the selected learning data and inputs the acquired topographical feature data and the speed of the vehicle to the prediction model M being trained. The prediction model M predicts the positioning error distribution corresponding to the input topographical feature data and the speed of the vehicle (step S13). For example, in a case where the prediction model M acquires an input parameter "A building having a height of 20 m exists in the north direction, and

the vehicle travels from west to east at a speed of 40 km/h on the road that runs from west to east on the south side of the building." that includes the topographical feature data and the speed of the vehicle, when the vehicle travels at the location having the same topographical feature with the same conditions, the prediction model M outputs a value close to the probability distribution of the actually observed positioning error.

[0032]

Next, the prediction model creation unit 12 performs the evaluation of the predicted value (probability distribution of positioning errors) (step S14). As described above, in the present disclosure, the evaluation of the predicted value is performed by using the failure rate instead of evaluating the difference between the probability distribution of the positioning errors output by the prediction model M and the probability distribution of the actually observed positioning errors. Specifically, first, the predicted value calculation unit 121 calculates the Dirichlet distribution (Y_{12} in Figs. 2(b) and 3(b)) by using the number of times of observation of each of the positioning errors of the learning data, the total number of times of observation, and the equation (2). Next, the predicted value calculation unit 121 calculates the

distribution of the observation failure rates (W in Figs. 2(c) and 3(c)) by generating a random number based on the Dirichlet distribution and using the random number and the equation (3). Next, the evaluation unit 122 calculates the failure rate f_{pred} (f_{pred} in Figs. 2(b) and 3(b)) based on the predicted values by using the equation (1) and the predicted values (Z_{12} in Figs. 2(b) and 3(b)) predicted by the prediction model M being trained in step S13. Thereafter, the evaluation unit 122 calculates the evaluated value L (L_w in Figs. 2(c) and 3(c)) by using the equation (4).

[0033]

Next, the update unit 123 updates the parameter of the prediction model M so as to maximize the evaluated value L (step S15). Next, the prediction model creation unit 12 determines whether or not an end condition is satisfied (step S16). For example, the prediction model creation unit 12 determines that the end condition is satisfied when the value of the evaluated value L reaches a predetermined target value. Alternatively, the prediction model creation unit 12 determines that the end condition is satisfied when the number of times of learning (the number of times of execution in steps S12 to S15) reaches a predetermined threshold value. When the end condition is not satisfied (step S16: No), the

prediction model creation unit 12 repeats the process from step S12. When the end condition is satisfied (step S16: Yes), the prediction model creation unit 12 ends the creation process of the prediction model M. The prediction model creation unit 12 records the trained prediction model M in the storage unit 13.

[0034]

According to the present embodiment, by using the failure rate as an index of the evaluation function, it is possible to create a positioning error prediction model that can appropriately evaluate whether or not the road on which the vehicle travels can be correctly recognized.

In the above example, it is decided to create the prediction model M that predicts the probability distribution of the positioning errors by inputting the topographical feature data and the speed of the vehicle, but the prediction model creation unit 12 may be configured to create the prediction model M that predicts the probability distribution of the positioning errors when the topographical feature data is input. This also applies to a second embodiment.

[0035]

<Second Embodiment>

Next, a prediction model creation device according to the second embodiment will be described with reference

to Figs. 5 to 7.

Fig. 5 is a diagram showing an example of the prediction model creation device according to the second embodiment of the present disclosure. The prediction model creation device 10A includes a data acquisition unit 11, a prediction model creation unit 12, a storage unit 13, and a reliability evaluation unit 14. The description of the same configuration as that of the first embodiment will be omitted.

[0036]

The reliability evaluation unit 14 evaluates the reliability of the probability distribution of the positioning errors predicted by the prediction model M. The reliability evaluation unit 14 executes either or both of (1) evaluation of the reliability based on the uncertainty of the model and (2) evaluation of the reliability based on the total number of times of observation when the model is being trained.

[0037]

(1) Evaluation of the reliability based on the uncertainty of the model

When the prediction model M is a network such as RNN, the reliability evaluation unit 14 applies a method called a dropout in which a part of the elements of the network is intentionally omitted. For example, the reliability

evaluation unit 14 performs the dropout a predetermined times using different networks each time and records the predicted value output by the prediction model M to which the dropout is applied for the same input. The reliability evaluation unit 14 evaluates the variation of the predicted value output by the prediction model M. When the variation is large, the reliability of the probability distribution of the positioning errors predicted by the prediction model M is evaluated as low, and when the variation is small, the reliability is evaluated as high.

[0038]

(2) Evaluation of the reliability based on the total number of times of observation when the model is being trained

As described with reference to Fig. 3(c), in a case where the total number of times of observation is large when the model is being trained, the evaluated value L greatly decreases when the predicted value f_{pred} is far from the distribution W of the observation failure rate. On the contrary, as described with reference to Fig. 2(c), in a case where the total number of times of observation is small, even when the predicted value f_{pred} is far from the distribution W of the observation failure rate, the spread of the distribution W is large so that the decrease

in evaluated value L is small. By utilizing the characteristics, the Dirichlet distribution in the equation (2) is used as the evaluation of reliability based on the number of times of observation when the model is being trained. However, since the n_k ($k = 2, 3, \dots, 11$) corresponding to the predicted value does not exist after the prediction model M is created, the Dirichlet distribution is calculated by using $n_k = N \times r_k$. When the spread of the Dirichlet distribution is large, the reliability evaluation unit 14 evaluates that the reliability of the probability distribution of the positioning errors predicted by the prediction model M is low (the total number of times of observation is small), and when the spread is small, the reliability evaluation unit 14 evaluates that the reliability is high (the total number of times of observation is large).

[0039]

Fig. 6 is a diagram for describing an evaluation method of the prediction model according to the second embodiment of the present disclosure.

Figs. 6(a) to 6(c) are diagrams for describing an evaluation process when the total number of times of observation is large. Fig. 6(a) shows a space of a feature quantity. The feature quantity is a parameter to be input to the prediction model. A point H_1 indicates an

input parameter in which a value of the feature quantity g_1 (for example, the topographical feature quantity) is G_1 and a value of the feature quantity g_2 (for example, the speed of the vehicle) is G_2 . Fig. 6(b) shows a space of the positioning error distribution. A point I_1 indicates an output when the input parameter of the point H_1 is input to the trained prediction model M , that is, the probability distribution of the positioning errors. The distribution J_1 indicates either or both the variation that occurred when the dropout is applied and the variation according to the total number of times of observation. The reliability evaluation unit 14 records the predicted value when the input parameter of the point H_1 is input in the storage unit 13 by applying the dropout to the trained prediction model M . The reliability evaluation unit 14 calculates $n_k = N \times r_k$ ($k = 2$ to 11) by using $r_2, r_3, \dots, r_{11}$ (probability in which each of the positioning errors = 2, 3, ..., 11[m] is observed) indicated by I_1 and the total value N (N is known) of the number of times of observation when the prediction model is created. Thereafter, the reliability evaluation unit 14 calculates the distribution of the posterior probabilities (Dirichlet distribution) of the positioning errors when each of the positioning errors of 2 to 11[m] is observed n_k ($k = 2$ to 11) times by using n_k, r_k, N , and

the equation (2). The reliability evaluation unit 14 records the calculated distribution of the posterior probabilities in the storage unit 13. The distribution J_1 is either or both a result obtained by plotting the predicted value recorded when the dropout is applied and the calculated distribution of the posterior probabilities. When the distribution W_1 of the observation failure rate is calculated based on the distribution J_1 , the distribution as shown in Fig. 6(c) is obtained.

[0040]

Figs. 6(d) to 6(e) are diagrams for describing an evaluation process when the total number of times of observation is small. Fig. 6(d) shows a space of the feature quantity, and Fig. 6(e) shows a space of the positioning error distribution. The point I_2 is the predicted value when the input parameter of the point H_2 is input to the trained prediction model M . The distribution J_2 for the predicted value I_2 indicates either or both the variation that occurred when the dropout is applied and the variation according to the total number of times of observation. The reliability evaluation unit 14 calculates the distribution J_2 in Fig. 6(e) by performing the same process as the process described in Fig. 6(b). When the distribution W_2 of the observation failure rate is calculated based on the distribution J_2 , the

distribution as shown in Fig. 6(f) is obtained.

[0041]

The reliability evaluation unit 14 evaluates the reliability of the predicted value based on the size of the spread of the distribution J_1 and the distribution J_2 . For example, by comparing the area of distribution J_1 and distribution J_2 with a predetermined threshold value, the reliability evaluation unit 14 evaluates that the reliability of the predicted value I_1 predicted by the prediction model M is high based on the fact that the area of the distribution J_1 is less than the threshold value. For example, the reliability evaluation unit 14 evaluates that the reliability of the predicted value I_2 predicted by the prediction model M is high based on the fact that the area of the distribution J_2 is equal to or larger than the threshold value.

[0042]

Next, the flow of the evaluation process of the predicted value will be described.

Fig. 7 is a flowchart showing an example of the evaluation process of the prediction model according to the second embodiment of the present disclosure.

First, the reliability evaluation unit 14 performs the evaluation of the reliability based on the uncertainty of the model (step S21). With respect to a certain

predicted value, the reliability evaluation unit 14 inputs the input parameter n value when the predicted value is obtained into the prediction model M to which the dropout is applied, and acquires the predicted value. The reliability evaluation unit 14 calculates the variation of the predicted value by performing the same process a plurality of times by changing the network in which the dropout is performed.

Next, the reliability evaluation unit 14 performs the evaluation of the reliability based on the total number of times of observation when the model is being trained (step S22). The reliability evaluation unit 14 calculates $n_k = N \times r_k$ with respect to the predicted value f_{pred} to be evaluated and calculates the distribution of the posterior probabilities from the equation (2).

Next, the reliability evaluation unit 14 evaluates the predicted value (step S23). The reliability evaluation unit 14 evaluates the reliability of the predicted value based on the size of the distribution obtained in steps S21 and S22.

[0043]

According to the present embodiment, in addition to the effect of the first embodiment, the reliability of the predicted value predicted by the trained prediction model M can be evaluated. For example, when the reliability of

the predicted value is low, as shown in Fig. 6(f), the distribution W_2 of the failure rate calculated based on the predicted value has a certain spread or more. In such a case, by checking the spread of the distribution W_2 , it is possible to make a determination such as "it is better not to perform a process related to road-charging because the failure rate is uncertain at the location and there is a possibility of misrecognition of the road".

[0044]

Fig. 10 is a diagram showing an example of a hardware configuration of the prediction model creation device according to each embodiment of the present disclosure.

A computer 900 is, for example, a personal computer (PC), a server terminal device, or the like including a CPU 901, a main storage device 902, an auxiliary storage device 903, an I/O interface 904, and a communication interface 905. The above-mentioned prediction model creation devices 10 and 10A are mounted on the computer 900. An operation of each processing unit described above is stored in the auxiliary storage device 903 in the form of a program. The CPU 901 reads the program from the auxiliary storage device 903, loads the program into the main storage device 902, and executes the above processes according to the program. The CPU 901 secures a storage

area corresponding to the storage unit 13 in the main storage device 902 according to the program. The CPU 901 secures a storage area for storing the data being processed in the auxiliary storage device 903 according to the program.

[0045]

In at least one embodiment, the auxiliary storage device 903 is an example of a non-temporary tangible medium. Other examples of non-temporary tangible media include a magnetic disk, a magneto-optical disk, a CD-ROM, a DVD-ROM, a semiconductor memory, and the like, which are connected via the I/O interface 904. When this program is distributed to the computer 900 by a communication line, the computer 900, which is received the distribution of the program, may load the program into the main storage device 902 and execute the above processes. The program may be for implementing a part of the above-mentioned functions. Further, the program may be a program that implements the above-mentioned function in combination with another program already stored in the auxiliary storage device 903 and may be a so-called differential file (differential program).

[0046]

In addition, it is possible to replace the components in the above-described embodiment with well-

known components as appropriate without departing from the spirit of the present invention. The technical scope of the present invention is not limited to the above-described embodiments, and various modifications can be made without departing from the spirit of the present invention.

[0047]

<Additional Notes>

The prediction model creation devices 10 and 10A, the prediction model creation method, and the program described in the embodiment are ascertain as follows, for example.

[0048]

(1) The prediction model creation devices 10 and 10A according to a first aspect are prediction model creation devices that create a prediction model for predicting a positioning error indicating an error in a position measured by a satellite positioning system, the prediction model creation devices include: a data acquisition unit 11 that acquires topographical feature data indicating a topographical feature of a certain location, the positioning errors with respect to positions of a moving body observed by the satellite positioning system when the moving body passes the location a plurality of times, and the number of times of observation for each of the

positioning errors; a prediction model creation unit 12 that creates a prediction model M for outputting a probability distribution of the positioning errors when the topographical feature data is input; an evaluation unit 122 that calculates an evaluated value of a failure rate, which is calculated based on a predetermined function (the equation (1)) and the probability distribution of the positioning errors output by the prediction model M and indicates a degree of possibility of occurrence of misrecognition with respect to the positions, based on an observation failure rate calculated based on the function (the equation (3)) and the number of times of observation for each of the positioning errors; and an update unit 123 that updates the prediction model M such that the evaluated value becomes an optimal value.

As a result, it is possible to create the prediction model M for predicting the positioning error for which an accurate failure rate can be calculated. The predetermined function indicates a function for calculating the failure rate, and the equation (1) or the equation (3) corresponds to the predetermined function.

[0049]

(2) The prediction model creation devices 10 and 10A according to a second aspect are the prediction model creation devices 10 and 10A of (1), the devices further

include a predicted value calculation unit 121 that calculates a distribution W of the observation failure rates based on the function (the equation (3)) and a distribution of posterior probabilities of the positioning errors for making the number of times of observation for each of the positioning errors equal to the number of times of observation acquired by the data acquisition unit 11, and outputs the distribution W as a predicted value of the failure rate.

As a result, it is possible to calculate the true distribution of the failure rates.

[0050]

(3) The prediction model creation devices 10 and 10A according to a third aspect are the prediction model creation devices 10 and 10A of (1) to (2), in which the evaluation unit 122 calculates an area L_w , in which a region having a predetermined width b centered on the failure rate calculated based on the prediction model M and a region occupied by a distribution W indicated by the predicted value of the failure rate overlap with each other, as the evaluated value L , and the update unit 123 updates a parameter of the prediction model M such that the evaluated value L is maximized.

As a result, it is possible to create the prediction model M that can calculate the accurate failure rate.

[0051]

(4) The prediction model creation device 10A according to a fourth aspect is the prediction model creation device 10A of (1) to (3), the device further includes a reliability evaluation unit 14 that evaluates a reliability with respect to a predicted value of the probability distribution of the positioning errors output by the prediction model.

[0052]

(5) The prediction model creation device 10A according to a fifth aspect is the prediction model creation device 10A of (4), in which when the prediction model M is constructed with a neural network, the reliability evaluation unit 14 performs evaluation of the reliability based on a variation at the time of applying a dropout to the prediction model when predetermined topographical feature data and a speed of the moving body are input to the prediction model.

[0053]

(6) The prediction model creation device 10A according to a sixth aspect is the prediction model creation device 10A of (4) to (5), in which the reliability evaluation unit 14 calculates a spread of a distribution of posterior probabilities of the predicted values based on a magnitude of a total value of the number

of times of observation, and performs the evaluation of the reliability based on the spread of the distribution.

According to the prediction model creation device 10A of the fourth to sixth aspects, it is possible to perform the evaluation of the predicted value output by the prediction model M even after the prediction model M is created.

[0054]

(7) A prediction model creation method according to a seventh aspect is a prediction model creation method for creating a prediction model for predicting a positioning error indicating an error in a position measured by a satellite positioning system, the prediction model creation method includes: an acquisition step of acquiring topographical feature data indicating a topographical feature of a certain location, the positioning errors with respect to positions of a moving body observed by the satellite positioning system when the moving body passes the location a plurality of times, and the number of times of observation for each of the positioning errors; and a creation step of creating a prediction model for outputting a probability distribution of the positioning errors when the topographical feature data is input, in which in the creation step of creating the prediction model, an evaluated value of a failure rate, which is

calculated based on a predetermined function and the probability distribution of the positioning errors output by the prediction model and indicates a degree of possibility of occurrence of misrecognition with respect to the positions, is calculated based on an observation failure rate calculated based on the function and the number of times of observation for each of the positioning errors, and the prediction model is updated such that the evaluated value becomes an optimal value.

[0055]

(8) A program according to an eighth aspect is a program for causing a computer to execute a process of a prediction model creation method for creating a prediction model for predicting a positioning error indicating an error in a position measured by a satellite positioning system, the process includes: an acquisition step of acquiring topographical feature data indicating a topographical feature of a certain location, the positioning errors with respect to positions of a moving body observed by the satellite positioning system when the moving body passes the location a plurality of times, and the number of times of observation for each of the positioning errors; and a creation step of creating a prediction model for outputting a probability distribution of the positioning errors when the topographical feature

data is input, in which in the creation step of creating the prediction model, an evaluated value of a failure rate, which is calculated based on a predetermined function and the probability distribution of the positioning errors output by the prediction model and indicates a degree of possibility of occurrence of misrecognition with respect to the positions, is calculated based on an observation failure rate calculated based on the function and the number of times of observation for each of the positioning errors, and the prediction model is updated such that the evaluated value becomes an optimal value.

[Industrial Applicability]

[0056]

According to the above-mentioned prediction model creation device, the prediction model creation method, and the program, it is possible to create a prediction model for estimating a distribution of errors in positions measured from positioning utilizing a satellite.

[Reference Signs List]

[0057]

10, 10A prediction model creation device

11 data acquisition unit

12 prediction model creation unit

121 predicted value calculation unit

122 evaluation unit

123 update unit
13 storage unit
14 reliability evaluation unit
900 computer
901 CPU
902 main storage device
903 auxiliary storage device
904 I/O interface
905 communication interface

Claims

[Claim 1]

A prediction model creation device that creates a prediction model for predicting a positioning error indicating an error in a position measured by a satellite positioning system, the prediction model creation device comprising:

a data acquisition unit that acquires
topographical feature data indicating a
topographical feature of a certain location,

the positioning errors with respect to
positions of a moving body observed by the satellite
positioning system when the moving body passes the
location a plurality of times, and

the number of times of observation for each of
the positioning errors;

a prediction model creation unit that creates a
prediction model for outputting a probability distribution
of the positioning errors when the topographical feature
data is input;

an evaluation unit that calculates an evaluated
value of a failure rate, which is calculated based on a
predetermined function and the probability distribution of
the positioning errors output by the prediction model and

indicates a degree of possibility of occurrence of misrecognition with respect to the positions, based on an observation failure rate calculated based on the function and the number of times of observation for each of the positioning errors; and

an update unit that updates the prediction model such that the evaluated value becomes an optimal value.

[Claim 2]

The prediction model creation device according to Claim 1, further comprising:

a predicted value calculation unit that

calculates a distribution of the observation failure rates based on the function and a distribution of posterior probabilities of the positioning errors for making the number of times of observation for each of the positioning errors equal to the number of times of observation acquired by the data acquisition unit, and

outputs the distribution as a predicted value of the failure rate.

[Claim 3]

The prediction model creation device according to Claim 2, wherein

the evaluation unit calculates an area, in which a

region having a predetermined width centered on the failure rate calculated based on the prediction model and a region occupied by a distribution indicated by the predicted value of the failure rate overlap with each other, as the evaluated value, and

the update unit updates a parameter of the prediction model such that the evaluated value is maximized.

[Claim 4]

The prediction model creation device according to any one of Claims 1 to 3, further comprising:

a reliability evaluation unit that evaluates a reliability with respect to a predicted value of the probability distribution of the positioning errors output by the prediction model.

[Claim 5]

The prediction model creation device according to Claim 4, wherein

when the prediction model is constructed with a neural network, the reliability evaluation unit performs evaluation of the reliability based on a variation at the time of applying a dropout to the prediction model when predetermined topographical feature data and a speed of

the moving body are input to the prediction model.

[Claim 6]

The prediction model creation device according to Claim 4 or 5, wherein

the reliability evaluation unit

calculates a spread of a distribution of posterior probabilities of the predicted values based on a magnitude of a total value of the number of times of observation, and

performs the evaluation of the reliability based on the spread of the distribution.

[Claim 7]

A prediction model creation method for creating a prediction model for predicting a positioning error indicating an error in a position measured by a satellite positioning system, the prediction model creation method comprising:

an acquisition step of acquiring

topographical feature data indicating a topographical feature of a certain location,

the positioning errors with respect to positions of a moving body observed by the satellite positioning system when the moving body passes the

location a plurality of times, and

the number of times of observation for each of the positioning errors; and

a creation step of creating a prediction model for outputting a probability distribution of the positioning errors when the topographical feature data is input, wherein

in the creation step of creating the prediction model,

an evaluated value of a failure rate, which is calculated based on a predetermined function and the probability distribution of the positioning errors output by the prediction model and indicates a degree of possibility of occurrence of misrecognition with respect to the positions, is calculated based on an observation failure rate calculated based on the function and the number of times of observation for each of the positioning errors, and

the prediction model is updated such that the evaluated value becomes an optimal value.

[Claim 8]

A program for causing a computer to execute a process of a prediction model creation method for creating a prediction model for predicting a positioning error

indicating an error in a position measured by a satellite positioning system, the process comprising:

an acquisition step of acquiring

topographical feature data indicating a topographical feature of a certain location,

the positioning errors with respect to positions of a moving body observed by the satellite positioning system when the moving body passes the location a plurality of times, and

the number of times of observation for each of the positioning errors; and

a creation step of creating a prediction model for outputting a probability distribution of the positioning errors when the topographical feature data is input, wherein

in the creation step of creating the prediction model,

an evaluated value of a failure rate, which is calculated based on a predetermined function and the probability distribution of the positioning errors output by the prediction model and indicates a degree of possibility of occurrence of misrecognition with respect to the positions, is calculated based on an observation failure rate calculated based on the function and the number of times of observation for each of the positioning

errors, and

the prediction model is updated such that the evaluated value becomes an optimal value.