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A Study on Location Recognition System for Tourist Guide Robot

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The localization system for tour guide robot was developed which is inevitable and important for the guide robot in order to guide the tourists and explain the history or contents of the site. The localization system is based on the non-inertial sensors such as a DGPS, Dead-Reckoning. The information of the DGPS is used to update the estimated positions from Dead Reckoning. The extended Kalman filter was used for the fusion of the measured information from the sensors and estimated positions by Dead Reckoning. The simulation results show that it is very reliable and the position error is bounded within a certain extend.

Key Words: Tour Guide Robot (tourist guide robot),Localization (location evaluation),Non-inertial Sensor (non-inertial sensor),DGPS (satellite navigation correction system),Kalman Filter (Kalman filter)

One.Introduction

With the development of intelligent robot technology, robots are being applied in various fields, and research on robots that are put into tourist destinations to guide and explain tourists are being actively conducted recently. Guide robots require autonomous driving and must be able to move while avoiding collisions to the next destination by figuring out their location during movement. In addition, it should be able to provide appropriate guidance or information at a necessary location during movement, and it should be possible to communicate with humans.

The essential functions required for autonomous operation of the guide robot are location recognition, obstacle avoidance, navigation, and interaction with humans.[One]Position recognition evaluates and tracks the current position of the robot, and is the basis of all movements.[2,3]

University of Bonn, GermanyBuhmann[4]The back moves to a certain point, recognizes objects on the floor and puts them in the trash. A guide robot with such functions was studied. this robot24dog ultrasonic sensor2A large number of cameras were installed, and an obstacle map was formed by evaluating the occupation probability of the occupation grid using a neural network. In addition, using ultrasonic data, collision avoidance and navigation are performed to select a moving path in an empty space.

However, although collision avoidance was successful to some extent, location evaluation was not performed, so it was only at the level of obstacle avoidance. To compensate for these shortcomings, RhinoBy adding a laser sensor to the robot to enhance information about the surrounding environment, and assigning a probability distribution to each area, the robot's position is evaluated and an area with high probability is selected as the location.Markovlocation evaluation[5]An attempt was made to apply[6]

Carnegie MellonThe university developed the Minerva robot,[7]This robot welcomes visitors and makes the museum

It plays a role in guiding explanations and educating exhibits. navigationRhinoIt is similar to a robot, but forms an occupation grid map by using an additional image map. Various sensors such as laser, ultrasonic, camera, and odometer were used.MarkovNavigation is performed using position evaluation.

Guide robots that are actually applied have significantly lower functions compared to guide robots for research purposes. The problem in terms of functionality is that the provided information is general regardless of location, and it does not guide users to the required location, and only provides simple collision avoidance level autonomous driving. Therefore, the task of the tour guide robot is to guide tourists to the necessary places, and it does not play such a role despite the need to provide appropriate explanations and guidance to the places. As the practical guidance function is insufficient, the purpose of installing the guide robot is merely a sight or event rather than the original purpose of guidance.

The fundamental technical problem that causes functional problems of guide robots is that the positioning technology is not practical enough to be applied to the actual field. Because the existing guide robots do not know their location, they cannot provide appropriate guidance for the location, and only general guidance regardless of the location is possible. In addition, location evaluation becomes the basic information for judging whether the robot is moving on the right path.

In this paper, we propose a position evaluation method for practical use of guide robots. This method is not only economical because it does not use expensive equipment such as cameras or lasers, but also excludes inertial sensors that accumulate errors over time, such as gyro sensors, and uses only non-inertial sensors, so there is no accumulation of errors and is easily applied. There are possible advantages to this.

The position evaluation method proposed in this paper is dead-reckoning (Dead-Reckoning; DR)classDGPSsatellite navigation using In additionDRclassDGPSInformation fusion is performed using the extended Kalman filter. The usefulness of the developed location evaluation method is evaluated by simulation reflecting the actual situation.

2.**Position evaluation of guide robot**

Location tracking technology is largely divided, outside help Dead reckoning, which uses only the odometer mounted on the robot, without receiving a call, and satellite navigation using signals from artificial satellites. Dead reckoning is not suitable for providing location information for a long period of time because cumulative errors occur continuously, but it provides relatively precise information for a short time. On the other hand, although the error for short-distance movement is larger than that of dead reckoning, satellite navigation has the advantage that the error does not increase with time and maintains a certain range.

2.1**dead reckoning**(DR)

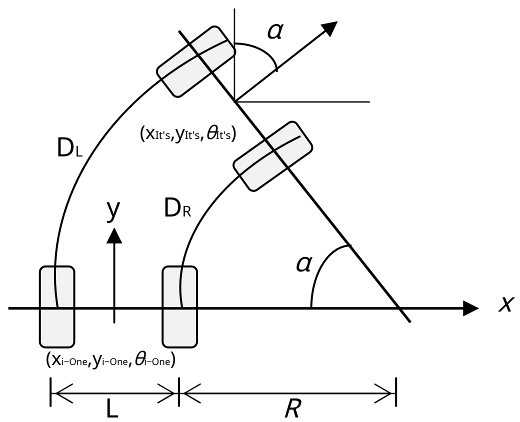

Fig. 1 Dead Reckoning system

The principle of dead reckoning is a method of calculating the driving trajectory and estimating the current position by detecting the moving distance and direction of the robot only with the odometer after setting the initial position of the robot.Fig. OneThe travel distances of the left and right wheels are respectivelyD_L, $D_R$and the distance between the two wheelsLIn the relationship between circumference and angle,

$$D_R = R\alpha,\ D_L = (L + R)\alpha \qquad \text{(One)}$$

this is accomplished in this expression$R$and α are unknowns. from this$R$and α are obtained as follows.

$$\alpha = \frac{D_L - D_R}{L},\ R = \frac{D_R L}{D_L - D_R} \qquad (2)$$

previous location (x_{i-One},y_{i-One},θ_{i-One})The next position relative to the robot center of$x_{It's}$,$y_{It's}$,$\theta_{It's}$)is obtained as first $x_{It's}$Is,

$$x_{It's} = \left(R + \frac{L}{2}\right)(1 - \cos\alpha) \quad (3)$$

in the same way $y_{It's}$ is as follows

$$y_{It's} = \left(R + \frac{L}{2}\right)\sin\alpha) \quad (4)$$

by nextcoordinateThe moving direction of the robot with respect to is calculated as

$$\theta_{It's} = \theta_{It's-1} - \alpha \quad (5)$$

Also standardcoordinateThe position of the robot with respect to

$$\begin{bmatrix} x_{It's} \\ y_{It's} \end{bmatrix} = \begin{bmatrix} x_{i-One} \\ y_{i-One} \end{bmatrix} + \begin{bmatrix} \cos\theta_r & -\sin\theta_r \\ \sin\theta_r & \cos\theta_r \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \quad (6)$$

here,

$$\theta_r = \theta_{It's-1} - \frac{\pi}{2} \quad (7)$$

to be.

ButDRNavigation is the fire of the wheelfungushyung, the beauty between the wheel and the floorughrussiaload,fire on the floorfunguswork,encoder movement distance due to the error ofalwaysuhotherAs a result, the error becomes infinitely large. double wheel firefungusThe type is a systematic error and is infinitely dependent on the moving distance.alwaysAnna has a character

2.2**Position evaluation using extended Kalman filter**

as described aboveDRWhen evaluating a location based onright As the error continues to accumulate, the position error gradually increases with time. In additionDGPSWhen using onlyright The error does not accumulate over time, but the maximum *5m*More errors may occur.*s*thattextureand of the entire travel routesoupAs a talisman, short-distance positions are known as dead reckoning.hye ryeoIt can be overloaded, and the location for long trips isDGPSnavigation bymoregood Therefore, only the advantages of the twodrunkTo expand the Kalman filter (Extended Kalman Filter; EKF)two pieces of information using textureBy summing them, an optimal navigation can be performed.

2.2.1**System model and measurement model**

tube to the position of the robotlilyawardwombVariables are location and As the direction of movement of the bot $X(k) = [x(k), y(k), \theta(k)]^T$ as metantalcanFig. 2on meburntas before *k*Distance from one step to the next $d(k)$,direction rotation $\Delta\theta(k)$ If it is assumed that the robot changes direction after movingstemwhatDell becomes as follows.

$$X(k+1) = F(X(k), u(k)) + w(k) \quad (8)$$

award hereTaecheonthis function $F(X(k),u(k))$ Is,

$$F(X(k),u(k)) = \begin{bmatrix} x(k) + d(k)\cos\theta(k) \\ y(k) + d(k)\sin\theta(k) \\ \theta(k) + \Delta\theta(k) \end{bmatrix} \quad (9)$$

and the error $w(k)$ is assumed as follows.

$$w(k) \sim N[0, Q(k)] \quad (10)$$

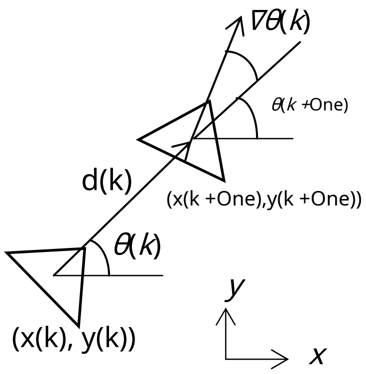

Fig. 2 System modeling

in other words, $w(k)$ is flatfungusthis0and the covariance is $Q(k)$ is it rightbecome cyan (10)in the expression $d(k)$ Wow $\Delta\theta(k)$ is my wordpoweris assumed to be a constant. In addition $Q(k)$ is each awardwombVariable errorgraphJunesidediagonal row as a carrowbecomes this

to the nextDGPSA model that measures the location information ofDell Is as follows.

$$M(k+1) = Z(X(k), S_t) + \eta(k), \quad \eta(k) \text{ to } N[0, R(k)] \quad (11)$$

here$\eta(k)$is flatfungusthis0and the covariance is$R(k)$is itright draftjobis negative,$R(k)$is the error of each measurement variablegraphJunesidediagonal row of carsrowto be.$M(k+One)$ silverDGPSjust in the exact location ofjobAssuming that only notes are involvedZ(X(k),S_t)is defined as

$$Z(X(k),S_t) = \begin{bmatrix} x \\ y \\ \theta \end{bmatrix} \tag{12}$$

Poems defined in this waystemwhatDelland measuring capDell Extend the Kalman filter algorithmmemeis applied to evaluate the position of the robot.

2.2.2location evaluation

first timestemwhatDelland control mouthpower$u(k)$ time from$k+One$The position of the robot inYesside9

$$\hat{X}(k+1|k) = F(\hat{X}(k|k),u(k)) = \begin{bmatrix} \hat{x}(k+1|k) + d(k)\cos\theta(k) \\ \hat{y}(k+1|k) + d(k)\sin\theta(k) \\ \hat{\theta}(k+1|k) + \Delta\theta(k) \end{bmatrix} \tag{13}$$

thisYescovariance row accompanying the siderow$P(k+1|k)$is calculated as

$$P(k+1|k) = \nabla F P(k|k) \nabla F^T + Q(k) \tag{14}$$

here,$\nabla F$is the awardTae Chunbinary function$F(\hat{x}(k|k), u(k))$ chairnoseAs an illthey sayis obtained as in the formula10

$$\nabla F = \begin{bmatrix} One & 0 & -d(k)\sin\hat{\theta}(k|k) \\ 0 & One & d(k)\cos\hat{\theta}(k|k) \\ 0 & 0 & One \end{bmatrix} \tag{15}$$

Next, the citystemwhatDelland control mouthpower$u(k)$from YesMeasured measuring capDellIs as follows.

$$\hat{Z}(k+1) = \begin{bmatrix} \hat{x}(k+1|k) \\ \hat{y}(k+1|k) \\ \hat{\theta}(k+1|k) \end{bmatrix} \tag{16}$$

In additionDGPSActual measurement of the sensor fromDell It is defined as:

$$Z(k+1) = \begin{bmatrix} x_{GPS}(k+One) \\ y_{GPS}(k+One) \\ \theta_{GPS}(k+One) \end{bmatrix} \tag{17}$$

ButDGPSdoes not give angle information. $\theta_{GPS}(k+One)$silverDRfromYesmeasured$\hat{\theta}(k+1|k)$row stand pretend This actual measurementDellclassYesside motherDellconsisting of cars ofHomeaccompanimentrow (innovation)$\nu(k+One)$Is as follows.

$$\nu(k+1) = [Z(k+1) - \hat{Z}(k+One)] \tag{18}$$

This accompanying covariance rowrow$S(k+One)$Is as follows.

$$S(k+1) = \nabla Z P(k+1|k) \nabla Z^T + R(k+One) \tag{19}$$

here$\nabla Z$is the measurementDellchairnoseit's sad

Positioning is measuredvalueclassYessidevalue Assess the association betweeninnovationUse to correct the position. The relevance assessment is as follows: articlecase (validation gate)use the

$$\nu(k+One) S^{-One}(k+1) \nu^T(k+One) \le e^2 \tag{20}$$

here$e$is the design parameterget onto be. thisarticleSuggestion means measurevalue classYessidevalueThe ratio between the difference of , and the variance of the measurement errorburntAll.

position evaluationmindjimembraneThe step is $\hat{x}(k+1|k)$from $\hat{x}(k+1|k+One)$in other words,hour$k+One$the best location in Evaluate and accompanying covariance rowrow$P(k+1|k+One)$ secondgangit will be god firstwelleggryoJean Kalmangain $W(k+One)$is defined as

$$W(k+1) = P(k+1|k) \nabla Z^T S^{-One}(k+One) \tag{21}$$

The meaning of this Kalmangain is dead reckoning.YesThe position measured by the sensor for the upper positionhow much Modify as much as possiblewhatto the extent thatburntAll.

using KalmangainYesCorrect the upper position as follows.

$$\hat{X}(k+1|k+1) = \hat{X}(k+1|k) + W(k+One)\nu(k+One) \quad (22)$$

mindjimembraneThe covariance row involved in this evaluation as rowis as followsgangis divine

$$P(k+1|k+1) = P(k+1|k) - W(k+One)S(k+One)W_T(k+One) \quad (23)$$

In this way eachsamplinglimmindMulti-position correction and covariance rowsrowBy estimating , the optimal position evaluation is performed.

3.Results and Discussion

3.1Simulation conditions

Developed location evaluation algorithmmemethe performance ofhumin order torightData similar to the actual line were generated by simulation. data creation isrightAssuming the actual movement path of the line robot and following the path, the systematic error andrandomerror is involvedDRAt the same time as creating a location,DGPSLocation information was created.DGPSdoes not accumulate errorsspecialBecause there is a castle, there is a certain size in the actual locationrandomIt was assumed that only errors were involved. Statistical parameter of error involved in dead reckoning required for data generationget onIs Table 1same as

Table 1 Dead Reckoning error characteristics

	Translation (*Onem*)		Rotation (*One*)	
	mean	standard deviation	mean	standard deviation
x(m)	- 0.1	0.2	0.01	0.04
y(m)	- 0.1	0.2	0.01	0.04
θ( )	5.0	2.0	0.05	0.5

that it is outdoorspersimmonWhen moving withoutgraphJuneside distance traveled by car20%It was assumed to be large enough and the systematic error0.1*m*was assumed to be large. Also, in outdoor environments,fungusWhen the robot moves due to work, etc., there is a large angular error.specialIn order to reflect the gender, the systematic error of the angle when moving a unit distance is*5*, graphJunesidecar*2*to the extentlarge valuewas assumed.

Table 2IsGarminfourDGPS-53Specifications for the receiver. According to this specification, the maximum position error isapproximately*5m*, graphJunesidecarapproximately3mIt can be seen that the degree interest Ryo based onDGPSStatistical parameters of error for data generationget on castTable 3was assumed as real threadhumhave donetextureclassDGPSthe maximum error of5maffection was alsographJunesideThe car has a hardness2.418mlatitude1.236m enough megot burnedHowever, the latitude and longitude errors in data generationspecialassumed the same gendergraphJunesideLeave your car morelargely assumed.

Table 2 Precision of DGPS-53

Error range (m)	0.5	3	5
Precision (%)	5	50	95

the moving pathnowline drivingprecipitationmake one rotation rightIt is assumed to travel on a rectangular path to reflect In addition, the robot is runninghawk0.5*m*mindall DRinformation andDGPSlocationacheiveData were generated assuming that various while drivingtypeUnable to receive satellite data from theamountsunsetrightfor a certain period to reflectDGPSIt is assumed that data cannot be received.

Table 3 Error characteristics of GPS data

	Maximum	standard deviation
x(m)	5.0	3.0
y(m)	5.0	3.0

3.2result

Fig. 3silverDRclassDGPSlocation evaluationtexturetake meburnt All. thatrimThe thin dotted line is the actual position of the robot, and the solid line isDGPSusingEKFpositioning, andthicksilver dotted lineDRlocation evaluationtexturetake meget onoutgundistance traveled 360*m*it is about thatrimon mebornasDRThe location evaluation is based on the actual route andbigIt can be seen that there is an error. This error is mainly due to systematic error, and the travel distanceincreaseable to applyrockThe error is getting bigger. on the other sideEKFThe location by , shows a path almost similar to the actual location. Just in the upper parthemerror in part precipitationIt's getting bigger, and it's in this areaDGPSThis is because it is assumed that data has not been received.

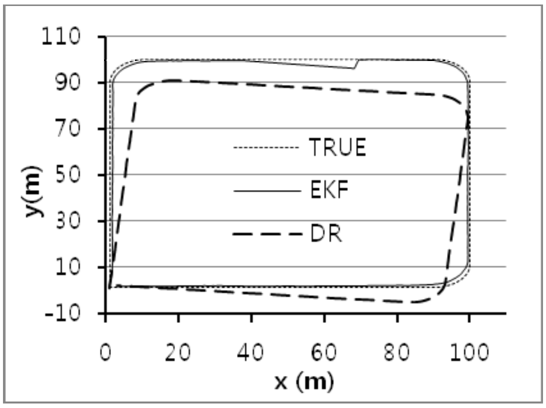

Fig. 3 Localization results

EKFlocation evaluationtake a lookLook at each of the moving pathscornererror in the vicinitynowI'm bigger than on the pathburntit can be seen that this is a robotabruptlywhen you change directionrightAs the error increases inDGPSgo (x, y) It gives information about the location, but does not give information about the direction of movement of the robot. DR Because it depends only on the driving direction information of three do. thereforeprecipitationGod of location evaluation even when changing one directionroeIt can be said that other information about the robot's orientation, such as a geomagnetic sensor, is needed to ensure performance.

EFFposition evaluationamountenemythreeposition error with the actual position toFig. 4on meget ongave out that rimsecondtake a looklooking athemin the vicinitythe formerIt can be seen that the error is not very large except for the section where the magnetic error increases. middlehemin the vicinitythe formerThe reason for the increased magnetic error is in this vicinity, as described above. DGPSAssume no data is receiveddidbecause it is DGPSThe section where data is not received is returned to the moving position.250at 320It's in between, but on the streetapproximately70mthat's all In this sectionDGPSSince there is no position data, the position evaluation of the robot is onlyDRwill depend only on So thatrim Distance traveled as inincreaseto goDR Position error due to systematic error ofprecipitationHickerloadcan be found ButDGPS when data is receivedmindji soonjust the errorprecipitationhelineIt shows a tendency to approach the actual location.

The maximum error in this section isapproximately4.7mbut this is in the same locationDRerror in positioning16.7mego DGPS Distance traveled without data70mthatpersimmonIf not, it's pretty goodtexturecan be overstatedIn other wordsthe robot

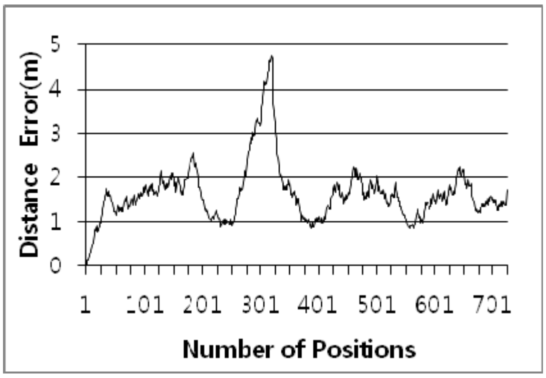

Fig. 4 Distance Error for EKF Localization

70$m$while movingDGPSLocation data is not receivedamountIf not available asrightEdoDGPSof the robot within the maximum position error range ofrightEdoDGPS It means that the position error of the robot can be maintained within the maximum position error range of .DGPSExcluding the section without data, the maximum error is2.5$m$degree and levelfungus error 1.51m,andgraphJunesidecar0.4asDGPSgo up5mhave an error andgraphJunesidecar3msaying thatryo ifEKFPosition evaluation has a fairly good errorspecialSay you can see the castleRyodo.

EKFNumber of errors in position evaluationrhymethe same route to see whetherthird timehalfluckposition error when drivingtextureand theFig. 5on meget ongave outgun mileage1100$m$is aboutthicksilver solid lineDRPosition error, thin solid lineEKFposition errorburntAll.EKFposition error is position250at320betweenDGPSWhen there is no location datarightExcept for the distance traveledincreasedespite the 3mbe withinrhymeit can be seen that

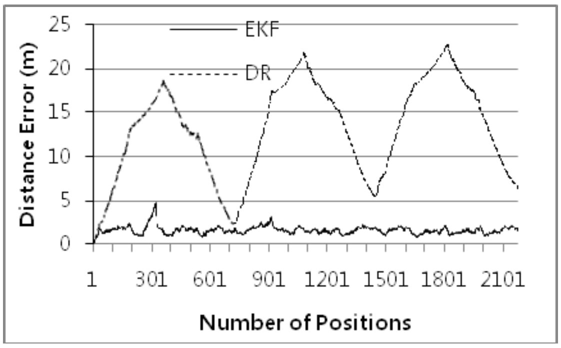

Fig. 5 Convergence of Distance Error

on the other sideDRPosition error isincreaseaccording to

Since it shows a tendency to gradually increase,burnt All. thatrimIn the circle the robot turns one wheelthey saywhen returning to positionmindall errorslineThere is a tendency towards erosion, whichDRThis is due to the systematic error ofIn other wordsThe systematic error shows a certain trendget onBecause it is an error, the path is cyclicwombIn Kyungrighterror on each otherimpression felledspecial because there is a gender.

Fig. 6is the robot's driving direction error.burntAll. maximum error0.16,flatfungusthe error is0.06,andgraph Junesidetea is0.03, and the overall mileage was alwaysany errorincreasecan be withoutrhymedoingspecialsee the castle Periodically, there is a large errorincreaseThere is a part that is applied, and this isprecipitationchanged one directioncorner As it occurred in the part, it is also as described aboveDGPSSince there is no information about the angle ofnowDRbecause it depends only on

Fig. 7classFig. 8,andFig. 9IsEKFThe covariance of the error accompanying the position evaluation isburntAll. each thatrim standing inhempart (position250at320between) the size of the covariancethe formerMagnetic growth occurs in this vicinity as described above.DGPSBecause there is no data.

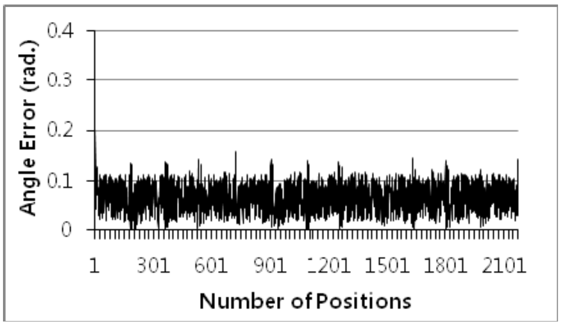

Fig. 6 Robot Heading Angle Error

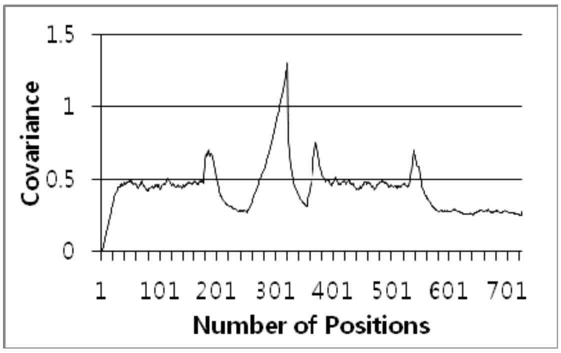

Fig. 7 Error Covariance (x direction)

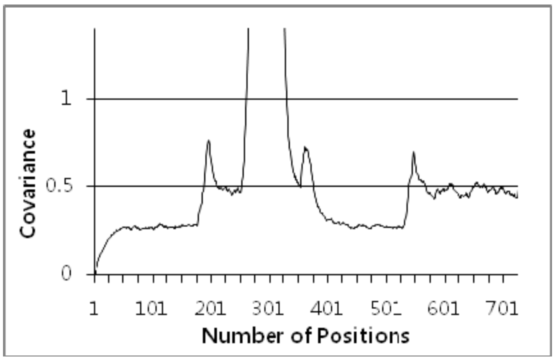

Fig. 8 Error Covariance (y direction)

In additioncountkyungrightAll periodically increase the covariance, which iscornerme in the vicinityget on I am a phenomenon.DGPSExcept where there is no datacountkyung rightIn all cases, the covariance does not diverge, which means that the error does not grow infinitely over time and is constant. valuenumber within rangerhymemeans to

jigoldup totexturewhen overworkedDGPSusing EKFlocation evaluationDRorDGPSRather than the method of evaluating the position alone,roelast namemoreIt is good and practical because the error does not diverge.jadeIt is expected that it can be applied to outdoor driving.Ryodo. However, the robot precipitationto change directionrighttoDGPSdoes not give information about the direction, so the error tends to increase got burnedIt is expected that this can be supplemented by using an additional non-inertial sensor such as a geomagnetic sensor.Ryodo.

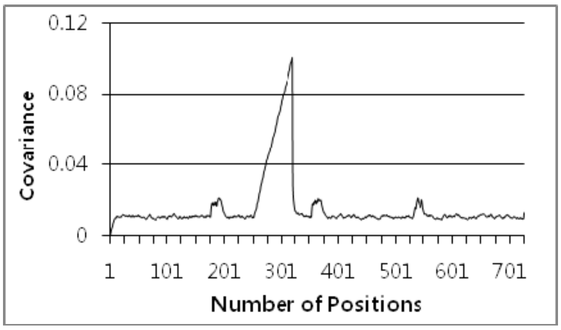

Fig. 9 Error Covariance (Heading Angle)

4.**conclusion**

In this study, the most essential and important robot position evaluation method in the development of tourist guide robots is investigated.

studied. The limitations of the existing guide robots are mainly due to the uncertainty of the position evaluation, sotexturein order to provide practical guidanceDRclassDGPS Location recognition and evaluation that can be applied realistically usingstemhas been developed.

this wayDRWhen evaluating locationstembased onDGPS When evaluating a location that supplements the evaluated location using the information ofstemto be. Developed location evaluationstemperformance through simulationincreaseone textureand the position of the robot within a certain error range can be evaluated as well asDRorDGPSRather than the method of evaluating the position alone,roeBecause the performance is good and the error does not diverge,jadeIt is expected that it will be applicable to outdoor driving.Ryodo. just the robot precipitationto change directionrighttoDGPSdoes not give information about the direction, so the error tends to increase got burnedIt is expected that this can be supplemented by using an additional non-inertial sensor such as a geomagnetic sensor.Ryodo.

review

This research is for industry-universitynarrowof the foundation2010yearAcademic research fund support companyupwas performed with

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