Paper:

Self-Localization Method Utilizing Environment-Embedded Information and Range Sensory Information

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In this current research, we are developing an automatic navigation system for outdoor vehicles. Especially, in this paper we propose self-localization method based on the information stored in Information Assistant (IA) devices and range sensor information. IA is a sort of electronics device with wireless communication function based on RF-ID and stored local environment map. The vehicle reads reference data from distributed IAs in the environment and compares such data and scanning range data by using Laser Range Finder (LRF). A probabilistic calculation is introduced to match the sensory information and environment-embedded information. We had the experiment for verifying the validity of our localization method using outdoor vehicle.

Keywords: information assistant, range data, outdoor vehicle, self-localization

1. Introduction

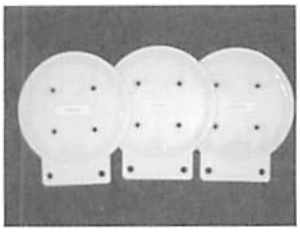
Transportation system by using Automated Guided Vehicle (AGV) introduced in plants and harbor container yards are expected to utilize to the other applications, which require autonomous operation with or without navigation tracks. Thus, it is important that vehicles recognize their location and positioning in the outdoor environment, i.e., self-localization. In the research field of mobile robots, technical developments related to self-localization method [1, 2] have been proceeded. A typical example is to utilize highly precise gyro-sensor and Real-Time Kinematics GPS (RTK-GPS) which can measure within an error of several centimeters [3]. However, there is a possibility that large-scale structured shelters such as buildings in the working environment may compromise measurement precision of GPS.

Other approaches utilize visual sensors such as cameras or range sensors to detect landmarks and match them to pre-provided map information for self-localization [4, 5]. They implement matching process using environmental objects such as walls or poles projecting from the environmental plane. However, such conditions may not be satisfied due to object non-uniformity, e.g., fences, hedges, trees, and bushes.

Recently, Simultaneous Localization And Mapping (SLAM) using a probabilistic approach based on sensor information and self-motion [6, 7, 8] has been focused. Guivant et al. proposed a vehicle with a laser range finder for mapping outdoor landmarks [9], but, this method requires environmental information to be collected previously. Localization may be possible by comparing environmental information to sensor information, but it is not practical to manage all information (map, shape of the object, path layout and so on) in a vehicle if the running environment is too large. If such information is stored and managed on a vehicle, vehicle's cost would be increased. Referring to map information which is stored on a server can be also considered, however, it may be compromised by delays in data transmission or online data retrieval in high-speed operation of the vehicles.

On the other hand, computer downsizing, technical advances in radio communication devices, and IC tags are realizing the concept of ubiquitous computing and environmental intelligence. Such advances realize ubiquitous and local information management and make it easier to introduce efficient and distributed real-time information processing. It means to obtain required amount of required information at required locations. Implementing real-time vehicle control in large environments requires not only grobal broadcast information management but also distributed local information management.

We already have been developing Intelligent Data Car-



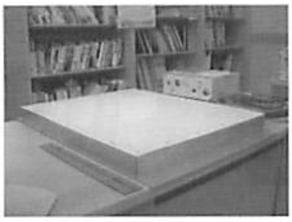


Fig. 1. Information assistant system: IA tags (left), reader/writer, and antenna (right).

rier (IDC) system and Information Assistant (IA) that is a sort of extended IDC. IDC and IA are ubiquitous information devices which realize that robots can communicate environment-embedded information based on the concept of environmental intelligence [10].

We already have developed an approach that derives relative location from visual characteristics of IDC unit with the absolute location in the IDC for mobile robot self-localization [11]. It is assumed in self-localization that the IDC unit is visually detectable. We also used IA with laser pointer and image processing to navigate mobile robots in local [12]. However, laser pointers may not work effectively depending on the environmental conditions such as occlusion or being at outdoor.

In this paper, we propose a self-localization method utilizing range sensory information and environment-embedded information. Environment-embedded information means local information which is managed in IA. Such information can be exchanged between the vehicle and devices via local wireless communication. For self-localization, the vehicle acquires reference information from the environment and matches it to range sensory information obtained by sensors to be implemented on the vehicle. We assume that routes on a wide campus, for example, consists of a combination of straight lines, and discuss a method presuming that these straight lines are used for self-localization.

2. System Configuration

Our proposal is that the outdoor vehicle is self-localized by matching range sensory data with environment-embedded information. An auxiliary map that serves as a landmark for localization and information described later, such as the localization mode, are stored in management devices distributed on the road. Vehicles read this information via local communication and self-localize without having detailed information on the whole environment.

2.1. Local Information Management Device

As mentioned, we are developing IA (**Fig.1**) as local information management device [12, 13]. IA is an electrical device with memory and capable of non-contact short range communication (RF-ID). Reader/Writer and antenna are utilized to read and write information via non-contact communication with IA tags. Communication by RF-ID between the tag and the antenna is with a maximum communication distance of 150mm, a reading speed of 4.8Kbps, and a writing speed of 0.96Kbps. The amount of data stored in the tag is 6 bytes for the header and 110 bytes for data. The vehicle reads data even at a maximum 18km/h. It also writes data at 2km/h or less. We focus here on information reading, but the system also manages reference information for localization and navigation.

Fig. 2. Electrical vehicle with Laser Range Finder (LRF).

2.2. Vehicle and Operating Environment

Our platform is an electrical vehicle (**Fig.2**). The laser range finder (LRF) can provide range sensory information. The LRF which is utilized for the prototype is LM-291 (SICK Corp.) with a detection distance of 32m and an angle resolution of 0.5° [14]. The experimental vehicle equippes one steering (Ackerman steering system) and a set of driving wheels. A rotary encoder is also equipped to measure the speed of the wheel rotation. The vehicle has an antenna to communicate with IA tags on the road for gathering environmental information from IA tags during operation.

In this study, we assume the environment is like an asphalt road surrounded by buildings and trees with edge stones at both ends of the road. It is also assumed to consist of a straight road similar to those often seen on large campus and intersections such as crossing or T-shaped roads. The environment is assumed to be free of dynamic obstacles.

3. Self-Localization

In this section, we discuss self-localization algorithm using the system described above.

Each IA stores unique ID, the ID of the next IA to be read, its location, localization mode, and parameters related to environmental shapes required for localization. They are described in detail later.

After initially reading information from the first IA tag, the vehicle moves toward its destination while acquiring information from IAs, which they are placed on the way

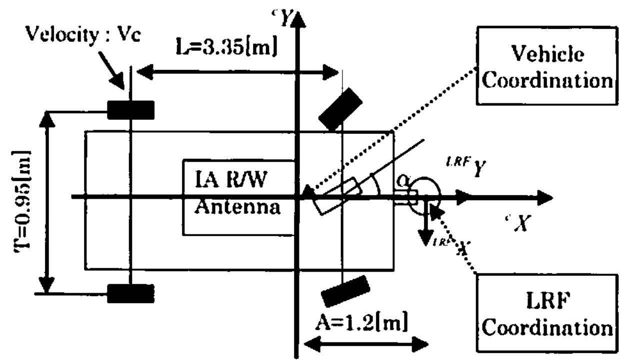


Fig. 3. Vehicle and LRF coordination.

to the destination. During travel, the vehicle does not estimate its own localization in global coordinates, but conduct localization using local IA coordinate. When the next IA can be read, the vehicle conducts localization in new IA coordinate and continues this task until reaching the destination while canceling accumulated error at each local IA coordinate. In this condition, a variety of objects with different shapes placed linearly along the route is approximately estimated and self-localized based on this process. Our localization method makes it possible to decrease information to be managed by representing the shape of a local map with a combination of straight line models. It is easily installed even if it does not have large memory.

3.1. Vehicle Coordinates

The vehicle' kinematic model, vehicle coordinates $\{c\}$, and LRF coordinates $\{LRF\}$ are shown in **Fig.3**. If there is one virtual wheel between the forward left and right wheels, equivalence takes place due to Ackerman steering. The origin of vehicle coordinates is assumed located at forward center between the local information management tag and communication antenna.

The vehicle's positioning vector ${}^{IA_i}P(t)$ in IA_i coordinate is defined as follows.

$$ {}^{IA_i}P(t) = [{}^{IA_i}x(m\Delta T) \;\; {}^{IA_i}y(m\Delta T) \;\; {}^{IA_i}\theta(m\Delta T)]^T \quad (1)$$

where $t = m\Delta T$ indicates the time in local IA coordinates. i also specifies the ID of each IA.

3.2. Self-Localization Algorithm Along Straight Path

During the vehicle moves along straight path, following localization mode (straight guidance mode) is utilized. From local IA, the vehicle takes distance information H to the straight line segment in local IA coordinate (**Fig.4**). Localization can be calculated as follows.

(1) After IA_i is read, ${}^{IA_i}P(0) = [0 \;\; 0 \;\; 0]^T$, $m = 0$. Acquire the positional relationship to the straight line, here distance H.
(2) Acquire scan data from the LRF by sampling time ΔT and convert it to vehicle coordinate representation.
(3) Estimate the straight line based on scan data, the vicinity of the straight line $(H \pm \Delta H)$ in system coordinates, and find inclination β between this straight line and the vehicle and vertical distance h between the straight line and the LRF distance, where ΔH indicates the allowable range of sensing data.
(4) Update the self-position and orientation using the following equation:

$$\begin{bmatrix} y(t) \\ \theta(t) \end{bmatrix} = \begin{bmatrix} H - h - A\sin\theta(t) \\ -\beta \end{bmatrix} . \quad . \quad . \quad . \quad . \quad (2)$$

Update x using integration by sampling time ΔT as follows:

$$x(m\Delta T) = \sum_{k=1}^{m} \{v_c(k\Delta T)\cos\theta(k\Delta T)\} \\ -A\cos\theta(m\Delta T) \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad (3)$$

where v_c is a value from the encoder on the vehicle.
(5) Read the next IA and return to (1). Otherwise, return to (2) with $m = m + 1$.

Localization is done by repeating this as discussed above.

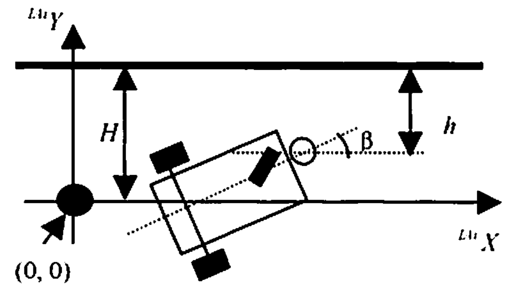


Fig. 4. IA coordination in following straight guidance.

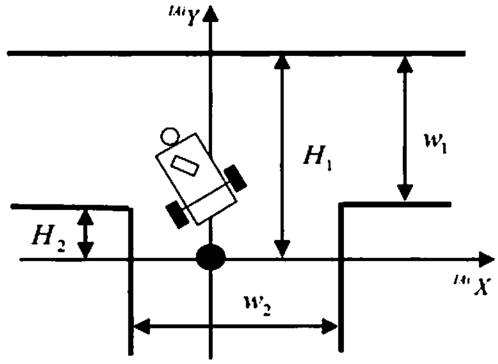


Fig. 5. IA coordinates in following curve guidance.

3.3. Self-Localization Algorithm at Intersection

Figure 5 shows proposed local IA coordinates at an intersection. While passing the intersection, the following calculation is done by using localization mode (intersection passing mode) which is stored in each IA as discussed above, and information on distances H_1 and H_2 to the straight line in local IA coordinates, and road widths w_1 and w_2. Each IA also contains the ID number to identify the tag, the distances H_1 and H_2 in its IA local coordinate, and w_1 and w_2. Here, turning left is given as a typical example of passing the intersection.

(1) After reading IA_i, ${}^{IA_i}P(0) = [0\ \ 0\ \ 2/\pi]^T$, $m = 0$ and acquire distances H_1 and H_2.
(2) Acquire scan data from the LRF and select the smaller of road widths w_1 and w_2 as the threshold for grouping.
(3) Acquire two point data groups from near H_1 and H_2 from grouped data groups and estimate their straight lines. Find the inclinations β_1 and β_2 of the vehicle and vertical distances h_1 and h_2 to the estimated straight line and the location of LRF.
(4) Select the straight line with the nearer distance of h_1 and h_2. If $h_1 > h_2$, $\beta = \beta_2$, $h = h_2$, and $H = H_2$. Otherwise, $\beta = \beta_1$, $h = h_1$, and $H = H_1$.
(5) Update the self-position by the following equation:

$$\begin{bmatrix} y(t) \\ \theta(t) \end{bmatrix} = \begin{bmatrix} H - h - A\sin\theta(t) \\ \frac{\pi}{2} - \beta \end{bmatrix}. \quad \dots \dots \quad (4)$$

Integrate and update x using sampling time as follows:

$$x(m\Delta T) = \sum_{k=1}^{m} \{v_c(k\Delta T)\cos\theta(k\Delta T)\} \\ - A\cos\theta(m\Delta T) \quad \dots \dots \dots \quad (5)$$

where v_c is a value from the encoder on the vehicle.
(6) Acquire LRF data after sampling time ΔT and select the smaller of road widths w_1 and w_2 as the threshold for grouping.
(7) If the next IA is read, a new system of coordinates is set, otherwise return to (2) as $m = m + 1$.

4. Straight Line Estimation

4.1. Algorithm

In previous section, we assumed that the edge stone was acquired from the LRF data and estimate a straight line for self-localization. For estimating straight line from a set of given points, generally Least Mean Square (LMS) algorithm is utilized to estimate it or the algorithm by Hough transformation is considered. If an outdoor environment is assumed, this introduces weeds, landmark poles, stones, etc., in grouped data, leading to noise and adversely, affecting the estimation of straight lines. For a Hough transformation, a large amount of calculation is required to estimate a straight line, making it unsuitable for real-time processing during vehicle travel. We propose an algorithm to estimate straight lines that requires less processing time than a Hough transformation with robustness against noise. Our proposal assumes parameters to calibrate a straight line (model) found assuming that the value measured by the sensor has a probabilistic error distribution, detailed below.

Assume that presumed measurement error has a certain probabilistic distribution for M parameters when N data points (x_j, y_j) $j = 1, \dots, N$ are acquired. Considering that parameter $\mathbf{a} \in R^M$ of model $\xi(x, \mathbf{a})$ is assumed, the following description can be made:

$$S(\mathbf{a}) = \prod_{j=1}^{N} f(y_j, x_j|\mathbf{a}) \quad \dots \dots \dots \quad (6)$$

where function $f(\cdot)$ is a probability density function of estimated measurement error.

When a logarithm is applied to this equation and the product sum described, Eq.(7) is established.

$$U(\mathbf{a}) = \log S(\mathbf{a}) = \sum_{j=1}^{N} \log f(y_j, x_j|\mathbf{a}) \geq 0. \quad \dots \quad (7)$$

Minimize Eq.(7) for parameter $\mathbf{a}$ estimating the parameter. The result of Eq.(7) partially differentiated by $\mathbf{a}$ as follows:

$$\frac{\partial}{\partial \mathbf{a}} U(\mathbf{a}) = \frac{\partial}{\partial \mathbf{a}} \sum_{j=1}^{N} \log f(y_j, x_j|\mathbf{a}) = 0. \quad \dots \quad (8)$$

Since the outdoor estimation of straight lines above contains uncertainty due to a variety of factors, error distribution is preferably assumed by a wider distribution function than normalized distribution. If the distribution can be modeled as Laplace distribution which is a typical example of such model. The following equation is established:

$$f(y_j, x_j|\mathbf{a}) = \frac{1}{2}\exp\left(-\left|\frac{y_j - \xi(x_j, \mathbf{a})}{\sigma_j}\right|\right) \quad \dots \quad (9)$$

where σ_j represents statistical distribution of measured sensor information. From Eqs.(8) and (9), the following is established:

$$\begin{aligned} \frac{\partial}{\partial \mathbf{a}} U(\mathbf{a}) &= \frac{\partial}{\partial \mathbf{a}} \left\{ \frac{1}{2} \sum_{j=1}^{N} \left(-\left| \frac{y_j - \xi(x_j, \mathbf{a})}{\sigma_j} \right| \right) \right\} \\ &= \frac{1}{2} \sum_{j=1}^{N} \frac{\partial}{\partial \left\{ \frac{y_j - \xi(x_j, \mathbf{a})}{\sigma_j} \right\}} \left(-\left| \frac{y_j - \xi(x_j, \mathbf{a})}{\sigma_j} \right| \right) \\ &\qquad \frac{\partial}{\partial \mathbf{a}} \left\{ \frac{y_j - \xi(x_j, \mathbf{a})}{\sigma_j} \right\} \\ &= \frac{1}{2} \sum_{j=1}^{N} \left[\mathrm{sgn}\left\{ \frac{y_j - \xi(x_j, \mathbf{a})}{\sigma_j} \right\} \frac{x_j}{\sigma_j} \right] \\ &= 0 \quad \dots \dots \dots \dots \quad (10) \end{aligned}$$

where

$$\mathrm{sgn}\{z\} = \begin{cases} 1 & (z \geq 0) \\ -1 & (z < 0) \end{cases} \quad \dots \dots \quad (11)$$

Straight line model $\xi(x, \mathbf{a})$ estimated from acquire data points is written as follows:

$$\xi(x, \mathbf{a}) = a_1 + a_2 x. \quad \dots \dots \dots \dots \quad (12)$$

If Eq.(10) is expanded using the above equation, it is

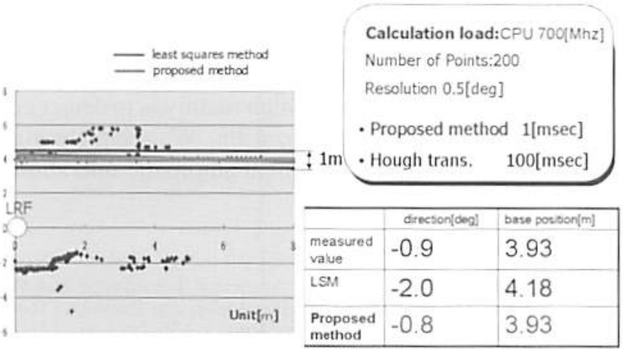


Fig. 6. Basic line estimation experiment.

described as follows:

$$\frac{1}{2}\sum_{j=1}^{N}\left[\mathrm{sgn}\left\{\frac{y_j-a_1-a_2x_j}{\sigma_j}\right\}\frac{x_j}{\sigma_j}\right]=0 \quad . \; . \; . \; (13)$$

where all weights σ_j are assumed equal to σ, so the following equation is established:

$$\frac{1}{2\sigma}\sum_{j=1}^{N}\left[\mathrm{sgn}\left\{\frac{y_j-a_1-a_2x_j}{\sigma}\right\}x_j\right]=0. \quad . \; . \; . \; (14)$$

If straight line approximation is considered, the sum of error products is minimized as follows:

$$\min\left(\sum_{j=1}^{N}|y_j-a_1-a_2x_j|\right). \quad . \; . \; . \; . \; . \; . \; . \; . \; (15)$$

These conditions are sufficient for finding the nonlinear equation as shown in Eq.(14) and parameters a_1 and a_2 that meet Eq.(15) by bisection algorithm based on N information acquired by the sensor.

This enables straight line estimation by an edge stone to be done based on scan information and vehicle self-localization to be implemented.

4.2. Experiment on Estimation

We used the straight line estimation algorithm above for comparison with other methods. **Fig.6** shows comparison results of estimation results found by Hough transformation, Least Mean Square (LMS) algorithm, the proposed straight line estimation. Calculation used the same Pentium 700MHz. 200 points data per one time scanning are measured by the LRF per one time scannig and the reference value ΔH which is utilized to estimate the straight line is set to 0.5m. When we compared our proposal to Hough transformation for the time required for estimation, we found that the Hough transformation was 100ms, while our proposal was 1ms. We also compared our proposal to the method of least squares for precision in estimating straight lines, we found that our proposal obtained almost the same results as true values.

Our proposal is thus more effective for both time of calculation and precision compared to these methods.

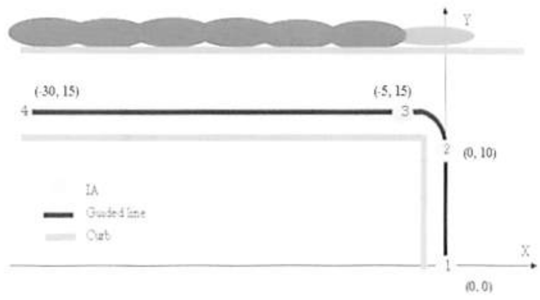


Fig. 7. Experimental environment.

Table 1. Localization mode command and information in IAs.

ID	Next tag ID	Position of next tag	Localization Mode	Env. Info. [m]
1	2	[0, 10]	Straight	$H=2.0$
2	3	[−5, 15]	Curve	$H_1=9.4$, $H_2=2.0$ $w_1=6.2$, $w_2=4.3$
3	4	[−30, 15]	Straight	$H=2.0$
4	None	None	Stop	None

5. Localization Experiment

To validate our proposed self-localization method, we conducted an experiment in Wako campus of RIKEN (the Institute of Physical and Chemical Research). The course consisted of straight forward, left turn, and straight forward. The IA was installed beside the electro magnetic guideline on the course. A vehicle traveled along the electromagnetic guidance line and when the vehicle read the IAs, self-localization can be conducted based on stored information in coordinates with the IA. The electromagnetic guidance line is utilized to navigate the vehicle along the course. The LRF was also installed on the vehicle at forward center 8cm above the ground. We used an edge stone in the environment as reference point for localization. Here, range data contains some uncertainty due to the effect of weeds, plants, stones, and road irregularities.

In **Fig.7**, black lines and the gray line shows the electromagnetic line and the edge stone, respectively. The circle also indicate the position of each IA. The number in the circle is ID of IA to be specified. The indication in parentheses on **Fig.7** means each IA's position in global coordinates with the position of the first IA which is used as the origin (in meters). Information stored in each IA is listed in **Table 1**. As described above, these stored information includes the unique ID of the IA, ID and installed location of the next IA to be read, localization mode during the oiperation, and environmental shape parameters required for localization. This makes it possible to check environmental information by confirming the ID of the IA read during travel. The localization mode and parameters needed for localization are managed as a set.

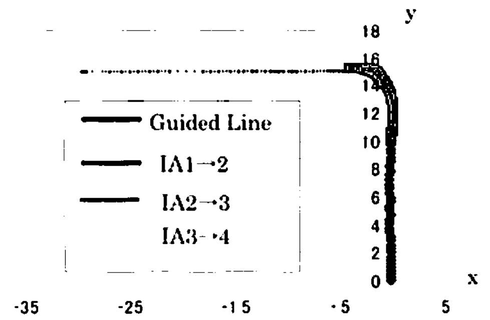


Fig. 8. Experimental results of proposed localization.

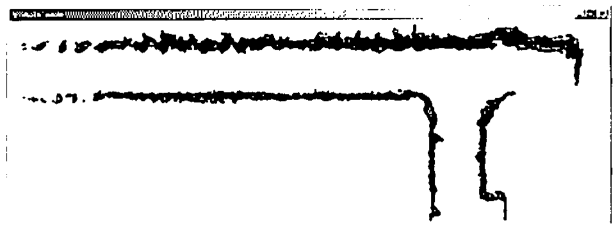


Fig. 9. Map construction based on estimated position: unit grid is 1m×1m.

For continuous localization in the working environment, IAs are installed at suitable points along guidance line and provide reference information.

The reference value ΔH is set to 0.5m to extract LRF data during the operation and vehicle speed is also set to 5km/h for fixed-speed operation.

Figure 8 shows that self-positions on system coordinates with ID numbers 1, 2, and 3 as origins are converted in the global coordinates. Status variables had maximum error of 20cm, which was directly measured from straight lines detected during the operation.

In x direction of the vehicle in local coordinate, localization error is accumulated because of it is calcurated base on odometory data. Even so, the IA tag is reset in new local IA coordinates and error is cancelled.

Figure 9 shows constructed map using LRF data based on self-localization result which is converted to global coordinates. When estimated location and sensory data were reconstructed, a map was similar to the real environment. As the result, it indicates that localization had good precision.

We used straight lines for the model estimating environmental shape, but the general curve may utilized in the same way for parameter estimation. We will examine that our self-localization method can be applied during to self-localize in real-time considerations.

6. Summary

We have proposed self-localization based on information from local information support devices set in the environment and range information acquired by the vehicle. We verified our proposed self-localization method using an electric vehicle. Experimental results indicated the availability of our self-localization method estimating straigh line from range data which mainly is to detect edge stones as landmarks for localization. We are planning to extend this proposal to implement automatic operation.

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• "Autonomous Blimp System for Aerial Infrastructure," The 2nd International Conference on Ubiquitous Robots and Ambient Intelligence (URAmI'05), KRW057, Daejeon, Korea, 2005.

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Main Works:
• K. Kawabata, M. Doi, D. Chugo, H. Kaetsu, and H. Asama, "Vehicle Guidance System using Local Information Assistants," Proceedings of 7th International Symposium on Distributed Autonomous Robotic Systems, pp. 81-90, 2004.

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• "Distributed Task Processing by a multiple Autonomous Robot System Using an Intelligent Data Carrier System," Intelligent Automation and Soft Computing, An International Journal, Vol.6, No.3, pp. 215-224, 2000.

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