The 2010 IEEE/RSJ International Conference on
Intelligent Robots and Systems
October 18-22, 2010, Taipei, Taiwan

Development of Motion Model and Position Correction Method using Terrain Information for Tracked Vehicles with Sub-Tracks

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***Abstract*— Gyro-based odometry is an easy-to-use localization method for tracked vehicles because it uses only internal sensors. However, on account of track-terrain slippage and transformation caused by changes in sub-track angles, gyro-based odometry for tracked vehicles with sub-tracks experiences difficulties in estimating the exact location of the vehicles. In order to solve this problem, we propose an estimation method with 6 degrees of freedom (DOF) for determining the position and pose of the tracked vehicles using terrain information. (In this study, position refers to the robot's position and pose.) In the proposed method, position are estimated using a particle filter. The subsequent position of each particle are predicted using a motion model that separately considers each contact point of the vehicle with the ground. In addition, each particle is analyzed using terrain and gravity information. Experimental results demonstrate the effectiveness of this method.**

I. INTRODUCTION

We are interested in the simultaneous localization and mapping (SLAM) problem of tracked vehicles on rough terrain. In order to solve this problem, a motion model that can predict the position of a robot in motion and a correction method for the accumulated errors of localization are required. In this study, the research target is localization, and the map for localization is known.

Tracked vehicles have attracted attention in the fields of civil engineering, architecture, and rescue. Figure 1 shows the tracked vehicle used in this study; it is called "Kenaf" [1]. Kenaf has been developed as a rescue robot. Kenaf has four sub-tracks that enable the vehicle to easily traverse stairs, steps, and concrete rubble. In this paper, we propose two models, one is a motion model that can be applied for example to a sub-track to predict the next position and the second model is a measurement model that corrects the accumulated errors of localization using terrain information.

In order to enable 3D localization for tracked vehicles on rough terrain, it is necessary to predict and correct the position of the robot while considering the contact points of the tracks with the ground. Odometry is a popular localization method used in mobile robots that move on flat ground. When traversal over flat ground is considered, it is assumed that the wheels come into contact with the ground at a single point and that the velocity at this contact point is tangential to the wheel, i.e., the direction of the velocity is the same as the direction in which the body of the robot faces. (In this paper, contact point refers to the contact point with the ground.) However, in the case of tracked vehicles, the contact points change depending on the surfaces of the land; further, since the track belts are flat, sub-tracks may come into contact with the ground. In these circumstances, the robot may move in a direction different from that in which the robot body faces.

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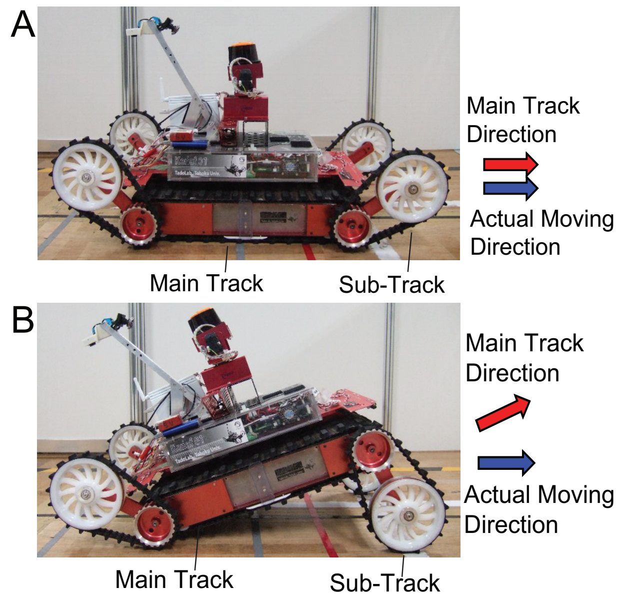

Fig. 1. Kenaf:Change of in the moving direction depending on sub-track angles.
(A:contact with the main track; B:contact with the sub-track)
When only the main track of the robot comes into contact with the ground (A), it is possible to estimate 6-DOF motion using odometry because the motion of the robot is in the direction that its body faces. However, in the case when both the main track and the sub-track come into contact with the ground (B), the robot does not move in the direction that its body faces; it moves in a direction parallel to the ground.

In such a case, the assumption of odometry that the robot moves in the direction in which its body faces is incorrect. In order to localize a tracked vehicle with sub-tracks, it is necessary to establish a model of its motion; this model should consider sub-track angles and land surfaces.

Figure 2 shows the concept of the measurement model of terrain information. The error in the position estimated using the motion model accumulates, and the estimated position may appear to be floating over or sinking into the ground. Although, in the case where it is assumed that the robot and its surroundings are rigid, the robot efficiently moves the surfaces since it cannot float or sink in the rigid ground. Therefore, it is possible to improve the accuracy of localization by correcting the estimated trajectory so that it

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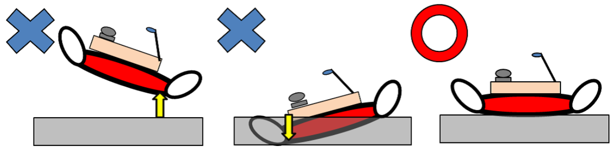

Fig. 2. States of contact of the robot and the ground and possible coordinates

moves on the surfaces of land that are detected by a 3D scanner mounted on the robot. The authors have proposed a localization method that can be effectively used in tracked vehicles with sub-tracks as it considers the contact points between the tracks and the ground. The main feature of the proposed method is that it can estimate contact points, which are otherwise difficult to be measured, using a particle filter. The robot position is estimated from these estimated contact points. Moreover, the accumulated errors of localization that occur due to using internal sensors are corrected using the assumption that a robot accurately moves on the surfaces of the land, and that the direction of the gravity as seen from a robot is measured using an acceleration sensor.

In order to realize real-time localization, a robot is approximated by points and the surfaces of the land using a digital elevation map (DEM). In an unknown environment, Kenaf can spontaneously get 3D visualization of the terrain from the 3D scanner mounted on it [2].

This paper is organized as follows: After discussing the related work in the next section, the authors briefly describe the proposed method in Section 3. The motion and measurement models for localization are presented in Sections 4, 5, and 6. In Section 7, the authors describe an experiment that was conducted to evaluate the accuracy of localization using the proposed method. Finally, in Section 8, the authors present experimental results illustrating the advantages of the proposed method.

II. Related Work

A. Localization Using Internal Sensors

The main feature of localization methods that use internal sensors is the ability to carry out localization without any pre-programmed environmental information. Therefore, it is possible to perform stable localization using internal sensors for an environment that has few landmarks.

Borenstein developed gyrodometry as an odometric model for wheeled robots [3]. In this method, a couple of rotary encoders and a gyro sensor cover mutually their shortcomings. When the angular velocities are small, they are calculated on the basis of the number of rotations because there is no slip for a robot. On the other hand, when the angular velocities are large, they are calculated using gyro sensors because the effects of errors associated with gyro drift are comparatively small.

Furthermore, Nagatani developed a method in which the rate of slip of track belts is estimated using a gyro sensor, and this method incorporated corrections for moving distances. Also, they developed ”3D gyro-based odometry”, which is a 3D localization method wherein moving distances and poses are estimated using gyro sensors [4]. This localization is highly accurate because it considers the slip between the tracks and the ground as a robot turns. Its drawback is the height errors that occur due to the inconsistency between the actual direction of motion of a robot and the assumption of 3D gyro-based odometry since sub-tracks are not considered.

In contrast, the motion model of the proposed method considers the changes in the direction of motion of a robot caused by sub-tracks because the direction of motion of the robot is estimated using the contacts points of both tracks with the ground.

B. Localization Using Internal Sensors and Map

Kummerle and Burgard developed a localization method for wheeled robots traversing over flat ground [5]. The method uses multilevel surface (MLS) maps and retains the assumption that a robot moves on the surfaces of the land. It is implemented using a particle filter, thus making it a probabilistic method. It can estimate the accurate position by translating the velocity vector, which is estimated using internal sensors, such that it indicates the position of the robot on the MLS map in the motion model. In the proposed method, contact with the ground is considered in the measurement model, and the contact points of the tracks and not those of the wheels are considered in the motion model.

Nakajima developed a localization method using the land profile [6]. This method searches the map for a position that fits the estimated trajectory of the robot. In this method, the longer the estimated trajectory, the higher is the accuracy of localization. A global localization is possible since an appropriate position for the estimated trajectory can be searched in any arbitrary area on the map. The major drawback of this method is that searching for the appropriate position is a very time consuming process. In contrast, the proposed method does not require continuity of the estimated trajectory, and the position is estimated by examining the possibility that the robot pose depends on the shape of the land.

C. Correction Using External Sensors and Map for localization

It is possible to correct the accumulated errors of localization using Laser Range Finder (LRF) [7], image sensor [8], ultrasonic sensor together with proposed method. The accuracy of local alignment, for example, Iterative Closest Point (ICP) algorithm [9], depends on the initial position of the observed data. The accurate motion model of a robot improves the accuracy of the estimation of robot position and map. This paper focuses on the motion model for robots with transformation mechanics and the position correction method using the contact condition between a robot and the land.

III. Localization Using Geometry of Robot and Environment

In this study, a particle filter is used for localization. Particle filters approximate the probability distribution of a Bayesian filter using the density of particles. The filters can be used to express various kinds of distribution. $\mathbf{x} = (x, y, z, \mathbf{q})$ is the position of the robot and $\mathbf{q} = (q_1, q_2, q_3, q_4)$ is a quaternion expressing the robot pose. In a Bayesian filter, the probability that the robot position is $\mathbf{x}_\mathrm{t}$ at time t, $p\left(\mathbf{x}_\mathrm{t} \middle| \mathbf{z}_{1:\mathrm{t}}, \mathbf{u}_{0:\mathrm{t}-1}\right)$, depends on measurements from 1 to t, $\mathbf{z}_{1:\mathrm{t}}$, and inputs from 0 to t-1 $\mathbf{u}_{0:\mathrm{t}-1}$. $\mathbf{u}_{0:\mathrm{t}-1}$ is updated from expression (1) [10].

$$\begin{aligned} & p\left(\mathbf{x}_\mathrm{t} \middle| \mathbf{z}_{1:\mathrm{t}}, \mathbf{u}_{0:\mathrm{t}-1}\right) \\ & = \eta p\left(\mathbf{z}_\mathrm{t} | \mathbf{x}_\mathrm{t}\right) \int p\left(\mathbf{x}_\mathrm{t} | \mathbf{u}_{\mathrm{t}-1}, \mathbf{x}_{\mathrm{t}-1}\right) p\left(\mathbf{x}_{\mathrm{t}-1}\right) d\mathbf{x}_{\mathrm{t}-1} \end{aligned} \tag{1}$$

$p\left(\mathbf{x}_\mathrm{t} | \mathbf{u}_{\mathrm{t}-1}, \mathbf{x}_{\mathrm{t}-1}\right)$ expresses the motion model predicting the next position of the robot. $p\left(\mathbf{z}_\mathrm{t} | \mathbf{x}_\mathrm{t}\right)$ expresses an measurement model correcting the robot position using the measured data. The most likely position is estimated by repeated prediction and correction. In this study, the authors propose the motion model considering contact points $p\left(\mathbf{x}_\mathrm{t} | \mathbf{u}_{\mathrm{t}-1}, \mathbf{x}_{\mathrm{t}-1}\right)$ and the measurement model using terrain information $p\left(\mathbf{z}_\mathrm{t} | \mathbf{x}_\mathrm{t}\right)$. The details of $p\left(\mathbf{x}_\mathrm{t} | \mathbf{u}_{\mathrm{t}-1}, \mathbf{x}_{\mathrm{t}-1}\right)$ and $p\left(\mathbf{z}_\mathrm{t} | \mathbf{x}_\mathrm{t}\right)$ are discussed in Sections 4 and 5. In the motion model for tracked vehicles, it is necessary to consider that tracked vehicles come into contact with the ground at several points. However, it is difficult to measure the contact points of tracks. Therefore, the contact points are estimated when the position is corrected using terrain information and the robot model approximated using representative points in the measurement model $p\left(\mathbf{z}_\mathrm{t} | \mathbf{x}_\mathrm{t}\right)$.

IV. Motion Model considering Contact Points

When the robot moves using its tracks, slip occurs because the velocities at all contact points are not equal. Therefore, the motion model of the proposed method assumes that one contact point has no slip and considers the velocity of that point.

Figure 3 shows the 3D motion model for tracked vehicles considering contact points. It considers a contact point P in the coordinate system. $\mathbf{v}$ is the velocity vector. $\mathbf{v}_\mathrm{P}$ is the velocity vector of the contact point $\mathbf{P}$, and l is the vector of the angular velocities of the robot and represents the rotation axes. The velocity $\mathbf{v}$ is derived on the basis of $\mathbf{v}_\mathrm{P}$; $\mathbf{v}_\mathrm{P}$ is given by expression (2).

$$\mathbf{v}_\mathrm{P} = \mathbf{v} + \omega \times \overrightarrow{\mathrm{OP}} \tag{2}$$

Expression (2) is re-arranged to obtain $\mathbf{v}$, and the result is given by expression (3).

$$\mathbf{v} = \mathbf{v}_\mathrm{P} + \omega \times \overrightarrow{\mathrm{PO}} \tag{3}$$

The velocity $\mathbf{v}_\mathrm{P}$ at the point P consists of the velocity of the track belt $\mathbf{v}_\mathrm{belt}$ and the velocity of slip $\mathbf{v}_{\mathrm{G-slip}}$.

$$\mathbf{v}_\mathrm{P} = \mathbf{v}_\mathrm{belt} + \mathbf{v}_{\mathrm{G-slip}} \tag{4}$$

Then, the velocity vector $\mathbf{v}$ in the coordinate system centered at the center of robot's bottom face is given by expression (5).

$$\mathbf{v} = \begin{bmatrix} v_x \\ v_y \\ v_z \end{bmatrix} = \mathbf{v}_\mathrm{belt} + \mathbf{v}_{\mathrm{G-slip}} + \omega \times \overrightarrow{\mathrm{PO}} \tag{5}$$

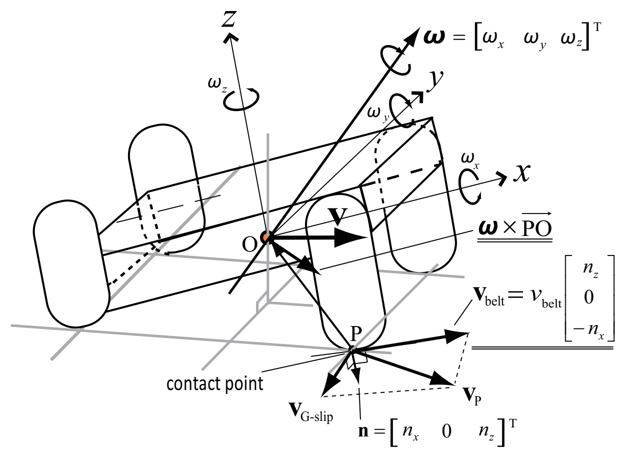

Fig. 3. 3D motion model for tracked vehicles considering contact points

The first term of (5) is the translational velocity produced at the contact point P due to the rotation of the track belt. The second term is the slip velocity. The third term is the translational velocity produced by rotation at the robot's center of gravity. When the robot does not slip, that is, when $|\mathbf{v}_\mathrm{belt}| = |v_\mathrm{belt}|$ and $\mathbf{v}_{\mathrm{G-slip}} = 0$, it is clear that only the velocity component tangential to the track belt exists. v_belt is the outer velocity of the track belt. $\mathbf{n} = [n_x, 0, n_z]^\mathrm{T}$ is the normal vector of the track at the contact point P, and the velocity $\mathbf{v}_\mathrm{belt}$ at P is represented by expression (6).

$$\mathbf{v}_\mathrm{belt} = v_\mathrm{belt} \begin{bmatrix} n_z \\ 0 \\ -n_x \end{bmatrix} \tag{6}$$

V. Measurement Model of Terrain Information

In this paper, the intended environment is like undergournd city consisting of things with little movement and deformation. Therefore the measurement model of terrain information is developed on the assumption that both the robot and its surrounding environment are rigid. In such the non rigid environment as rubble environment, it is impossible to assume that the environment is rigid. In this case, other methods are needed that recognizes the deformation of the land shape and stops the correction of the position using terrain information before the land shape is measured again.

In the rigid environment, the robot neither floats nor sinks in the ground. On the left in Fig 2, the robot floats, and in the center, it sinks in the ground. These states should be excluded from the localization process. The state shown on the right in Fig 2 where the robot comes in contact with the ground should be retained. These states are distinguished depending on the height of the bottom face of the robot from the ground. Hence, an approximated model of the robot is used in the proposed method.

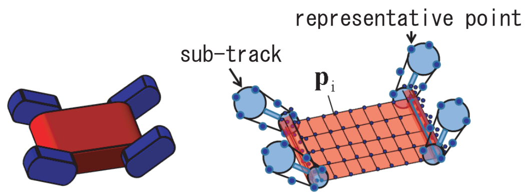

Fig. 4. Approximate robot model

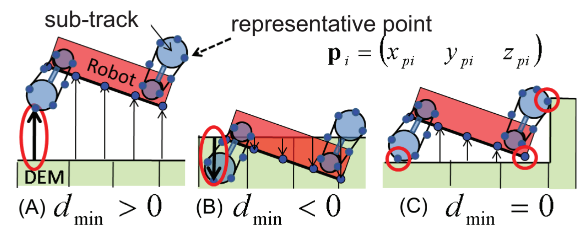

Fig. 5. Measurement model of terrain information

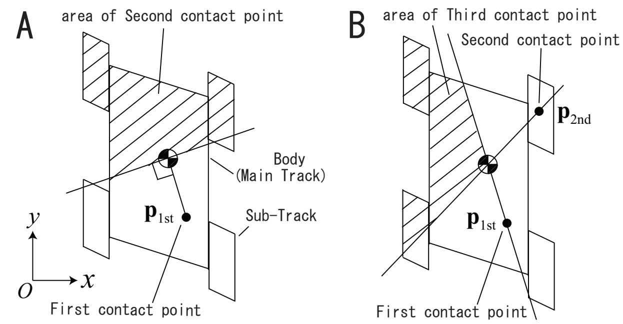

Fig. 6. Method for locating contact points. A: second point, B: third point

A. Approximate Robot Model

In the proposed method, the shape of the robot is approximated using representative points. In order to distinguish the different contact states of the robot, representative points $\mathbf{p}_i$ are marked all over the bottom face and sub-tracks of the robot, excluding the parts that have less possibility of coming in contact with the ground, for example, the upper face of the robot. The specific positions of the representative points are calculated according to the robot position and sub-track angles $\theta_{\text{sub}-\text{track}}$ (Fig 4). The distances between adjacent representative points are shorter than the length of the DEM grids. The approximated models enable faster calculation of distances between representative points of a robot and the corresponding DEM grids.

B. Weighing Using Terrain Information

In this study, minimum the length $d_{\min} = \min\left(z_{\mathbf{p}_i} - z_{\text{DEM}}\left(\mathbf{p}_i\right)\right)$ of the difference vector d from the DEM to the robot's representative points $\mathbf{p}_i$. $z_{\text{DEM}}\left(\mathbf{p}_i\right)$ is the height of the DEM grid corresponding to $\mathbf{p}_i$. The value of $d_{\min}$ is $d_{\min} > 0$ for the state shown in Fig 5.(A), $d_{\min} < 0$ for that shown in Fig 5.(B), and $d_{\min} = 0$ for that shown in Fig 5.(C). The error in $d_{\min}$ is determined by considering the measurement error of the shape of the land. In this study, $d_{\min}$ is the random variable of the measurement model of terrain information $w_{\text{DEM}}\left(d\right)$, and errors in $d_{\min}$ are approximated using Gaussian distribution. The average of the distribution obtained is 0 and the variance is ${\sigma_{\text{DEM}}}^2$. Each contact point is weighted using the expression (7).

$$w_{\text{DEM}}\left(d\right) = \frac{1}{\sqrt{2\pi}\sigma_{\text{DEM}}} \exp\left(-\frac{d^2}{2{\sigma_{\text{DEM}}}^2}\right) \tag{7}$$

Furthermore, the relation between the position of the robot's center of gravity and those of the contact points is discussed from the viewpoint of static stability of the robot. In the x–y plane, it is assumed that the robot's center of gravity lies in the plane containing the contact points; three contact points are chosen in the following manner:

First point:
: The representative point p_i such that $d(\mathbf{p}_\text{i}) = d_{\min}$.

Second point:
: The representative point p_j such that $d(\mathbf{p}_\text{j}) = d_{\min}$; this point is located in the area opposite the first point on the line perpendicular to the line joining the robot's center of gravity and the first point (Fig 6.A).

Third point:
: The representative point p_k such that $d(\mathbf{p}_\text{k}) = d_{\min}$; the robot's centre of gravity is located in the area bounded by the lines joining the first and second points and this point (Fig 6.B).

The distance $d_i(i = 1; 2; 3)$ between the ground and each contact point is calculated, and each particle is weighted using expression (8).

$$w_{\text{DEM}} = \prod_{i=1}^{3} w_{\text{DEM}}\left(d_i\right) \tag{8}$$

VI. Measurement Model of Acceleration Data

It is possible to correct a robot's pose using the direction of gravity measured with an acceleration sensor when the translational acceleration of the robot is either zero or has some estimable value. The angular difference α is the random variable of the measurement model of acceleration. It is the angle between the direction of the gravity as seen from each particle and the direction of gravity measured using the acceleration sensor (Fig 7). The distribution of the measurement model of the acceleration data is approximated as a Gaussian distribution. The average of the obtained distribution is 0 and the variance is ${\sigma_{\text{accel}}}^2$.

$$w\left(\alpha\right) = \frac{1}{\sqrt{2\pi}\sigma_{\text{accel}}} \exp\left(-\frac{\alpha^2}{2{\sigma_{\text{accel}}}^2}\right) \tag{9}$$

The nonlinearity of the acceleration sensor used in this study (Crossbow CXL04GP3) is $\pm$ 0.2% FS (FS: Full

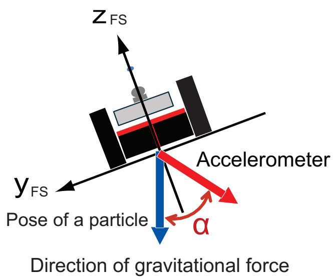

Fig. 7. Measurement model of acceleration data

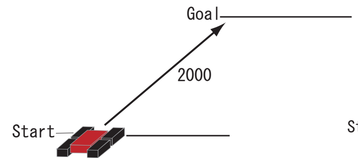

Fig. 8. Experimental path 1

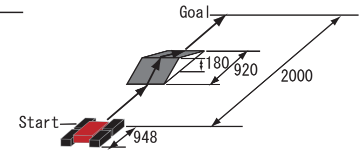

Fig. 9. Experimental path 2

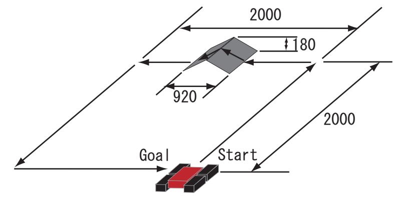

Fig. 10. Experimental path 3

Scale). Hence, the nonlinearity is ignored and its error is approximated using a Gaussian distribution because the magnitude of disturbances such as vibrations is larger than its measurement error.

VII. Experiment of Localization

In the first experiment, the accuracies of the proposed method and that of 3D gyro-based odometry are evaluated using motion capture trajectories. The second experiment is carried out to determine whether the localization of the proposed method is more accurate than the localization of 3D gyro-based odometry. In a wide area, the robot's position cannot be determined using motion capture. Therefore, a robot returns to the starting position, and the accuracy of localization is evaluated from the difference between the estimated starting and final positions. In the third experiment, it is confirmed that all three coordinates are corrected using the proposed method.

A. Implementation

In this experiment, the surfaces of the land is measured beforehand to generate a DEM in order to evaluate the accuracy of localization. The DEM grid width is 50 [mm]. The distance between the representative points of each robot is maintained at about 50 [mm] since it is comparable to the width of the DEM grid.

The next position of each particle is predicted from the outer velocity of the track belt and the angular velocities of the 3D velocity model. The direction of velocity at each contact point, estimated using the measurement model of terrain information, is tangential to the track belt (section IV). In this experiment, we ignore the slip velocity $\mathbf{v}_{\mathrm{G-slip}}$ that arises due to gravity when the robot navigates a slope and the translational velocity, $\omega \times \overrightarrow{\mathrm{PO}}$, caused by rotation about contact point P as the centre($\mathbf{v}_{\mathrm{G-slip}} = \omega \times \overrightarrow{\mathrm{PO}} = 0$); this is because the robot moves over a gentle slope. The weight of each particle is calculated using the distances from the representative points of the estimated position of a particle to the DEM; for this calculation, the measurement model of terrain information is used and the static stability of a robot is considered (Section V). The robot's position is corrected by resampling on the basis of the weight of each particle. Furthermore, information from the measurement model of gravity along with data from the acceleration sensor is used to correct the position of the robot (Section VI). By means of localization of the proposed method, repeated prediction and correction are carried out.

B. Experiment for Evaluation of Accuracy of Localization

The accuracies of the proposed method and 3D gyro-based odometry are evaluated with reference to the trajectories measured using motion capture. Figures 8 and 9 show experimental paths 1 and 2, respectively. For each path, Kenaf travels along a straight line for 2 [m], both with sub-tracks (Fig 1.B) and without sub-tracks (Fig 1.A).

Figures 11 and 12 show the trajectories estimated with and without sub-tracks using the proposed method and 3D gyro-based odometry, as well as the trajectories measured using motion capture for path 1; Figs 13 and 14 show the same for path 2. For the experiment without sub-tracks along path 1 (Fig 11), the trajectories estimated using the proposed method and 3D gyro-based odometry are similar to the trajectory measured using motion capture. However, for the experiment with sub-track along path 2 (Fig 12), the trajectory estimated using 3D gyro-based odometry shows considerable errors that arise due to inconsistency between the actual direction of motion and the assumption of 3D gyro-based odometry. In contrast, the trajectory estimated using the proposed method is similar to the trajectory measured using motion capture. Moreover, the displacement of the main track heaved by sub-tracks can be estimated using the proposed method (Fig 12, around 0 [mm]). The experiment along path 2 shows identical results (Fig 13). The difference between the results of experiments along paths 1 and 2 is that the pitch angle estimated using 3D gyro-based odometry shows a considerable error for motion over a slope. This error can be attributed to the error of the gyro in the measurement of pitch angle that arose when the robot's center of gravity moved to the top of slope and the robot toppled forward. This pose error can be corrected using the proposed method.

C. Experiment for Localization in Open Space

Figure 10 shows experimental path 3. Kenaf went around and returned to its starting position along path 3 (2 $\times$ 2 [mm]) with and without sub-tracks. Figures 15 and 16 show

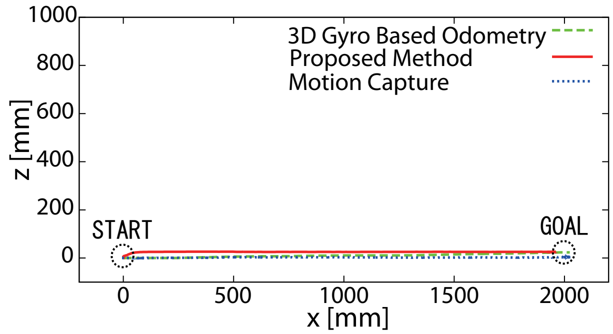

Fig. 11. Path 1: Trajectory without sub-tracks

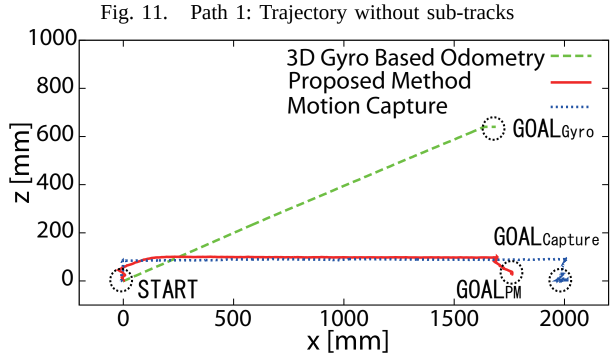

Fig. 12. Path 1: Trajectory with sub-tracks

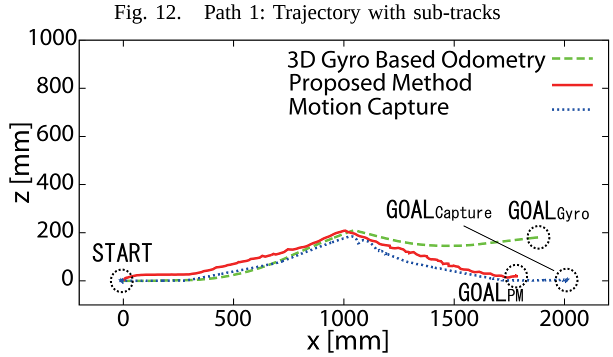

Fig. 13. Path 2: Trajectory without sub-tracks

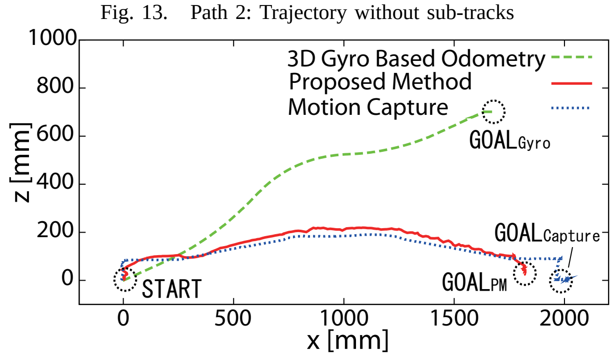

Fig. 14. Path 2: Trajectory with sub-tracks

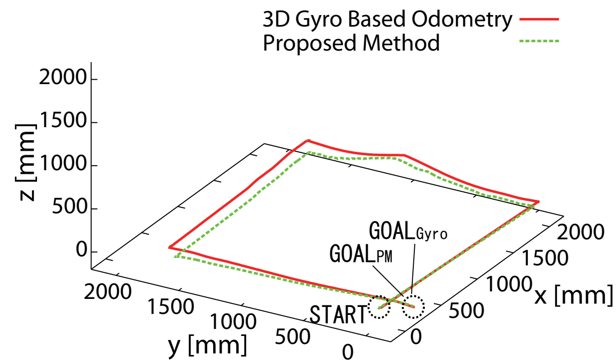

Fig. 15. Trajectory without sub-tracks

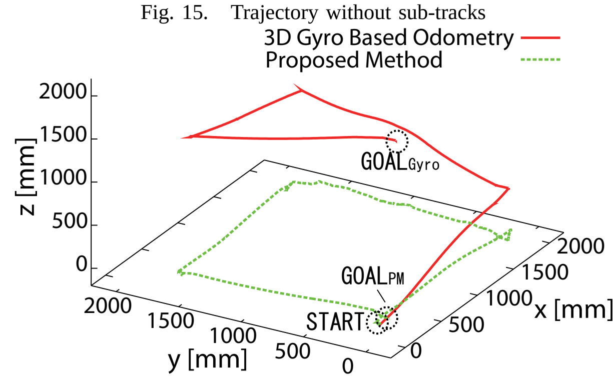

Fig. 16. Trajectory with sub-tracks

the trajectories estimated using the proposed method and 3D gyro-based odometry for the recorded time.

For the experiment without sub-tracks (Fig 15), the trajectories of the proposed method and 3D gyro-based odometry are similar, and both trajectories terminate at the starting point. However, for the experiment with sub-tracks (Fig 16), the trajectory of 3D gyro-based odometry shows a considerable height error. As in the case of paths 1 and 2, these errors can be attributed to the inconsistency between the actual direction of motion and the assumption of 3D gyro-based odometry. In contrast, the proposed method considers the change in contact points and hence minimizes the height error within a certain fixed range. Moreover, the trajectory estimated using the proposed method terminates at the starting point in a manner similar to the actual trajectory of a robot. Therefore, the proposed method is effective for use in a 3D environment.

D. Evaluation of Effectiveness for the Shape of the Land

In this experiment, it is confirmed that not only the z coordinates but also the x and y coordinates are corrected by the proposed method. The assumed initial variances are $\sigma_x = \sigma_y = 100$ [mm], $\sigma_z = 50$ [mm]. Figures 17 and 18 show paths 4 and 5, respectively. Kenaf went straight along each path. Figures 19 and 20 show the variances of x, y, and z with time.

Figures 19 and 20 show that the predicted value of z was corrected and the variances of z were minimized within a certain range. Along path 4 (Fig 19), the variances of y

decreased sharply around $x = 500$ [mm]. This was because the particles deviating along the y direction crashed into obstacles and were excluded from the localization process, while the particles passing between obstacles, as in the actual path, were included. Furthermore, the variances of x were minimized by obstacles, and the position was corrected in the front-to-back direction. Along path 5 (Fig 20), the variances of x and y reduced sharply around $x = 350$ [mm]. This occurred because the particles deviating along the x direction crashed into obstacles or floated off and were excluded from the localization process, while particles facing the front of the steps were included. Therefore, it was confirmed that the coordinates of x, y and z could be corrected using the proposed method.

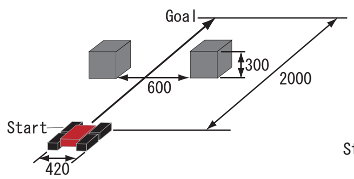

Fig. 17. Experimental path 4

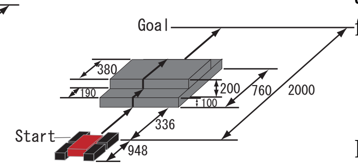

Fig. 18. Experimental path 5

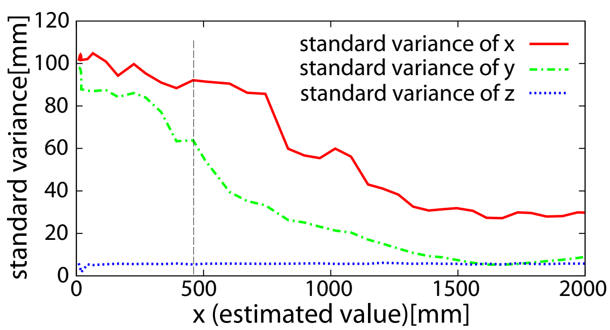

Fig. 19. Path 4: Standard variances

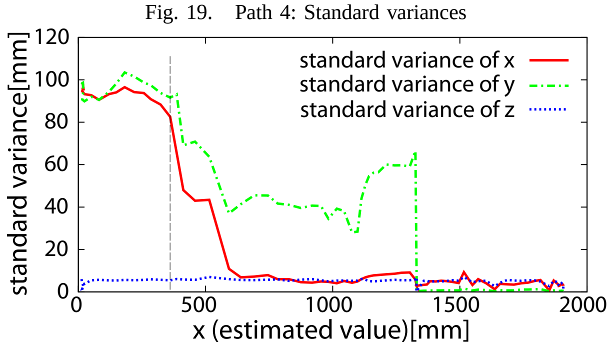

Fig. 20. Path 5: Standard variances

In this paper, the authors proposed a localization method for tracked vehicles with sub-tracks that considers the contact points of the tracks with the ground. The main feature of the proposed method is that the localization errors that accumulate when internal sensors are used are corrected by the assumption that a robot accurately moves on the surfaces of the land. In addition, the pose of the robot is corrected using the direction of gravity that is measured with an acceleration sensor. Furthermore, the authors proposed a motion model that considers the transformation and changes in the contact points of the robot; the contact points were estimated in the measurement model of terrain information. The proposed method was implemented on Kenaf and its effectiveness was confirmed.

Topics for future study include the development of a velocity model considering the slip ratio of each contact point. In this study, it was assumed that the track belt rotated without slipping at the contact point closest to the ground. However, the velocities of each contact point essentially depend on the condition of the road surfaces, position of the robot's center of gravity, and torque of each motor. At present, it is difficult to directly measure the contact pressure on each part of the track. Therefore, it is necessary to develop a method wherein the slip velocity is estimated from acceleration sensor data and the contact points are estimated from the terrain measurement model.

APOLOGIZE

This research has been partially supported by the NEDO Project for Strategic Development of Advanced Robotics Elemental Technologies, High-Speed Search Robot System in Confined Space, and MEXT Grant-in-Aid for Young Scientists (B) under contact numbers 21760181, 2010.

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