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Perception Based Locomotion System for a Humanoid Robot with Adaptive Footstep Compensation under Task Constraints

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***Abstract*— In order to accurately reach a target position while executing a task which imposes occlusion or constraints of the posture, a humanoid robot requires an adaptive locomotion system, which can comprehensively integrate localization, environmental mapping, global locomotion planning and local error correction. In this paper, we propose a method of constructing a perception based locomotion system for a humanoid robot. The major contribution of this paper is solving a problem of the locomotion error caused by the task constraints, by locally compensating footsteps and assessing the need for global footstep re-planning online based on environmental measurements. The proposed system provides an accurate and dense ground point cloud, called HeightField, using plane estimation and space interpolation, and obstacle point cloud for frequent collision avoidance by accumulating laser scans. This environmental perception enables a humanoid robot to plan footsteps globally even in the situation where the sight of the robot is limited and compensate footsteps while estimating landing state during locomotion online with the localization result. We evaluated the practicality of the proposed system by applying it to our humanoid robot carrying a heavy object in a construction site and confirmed that the proposed system contributed to improved locomotion abilities of a humanoid robot engaging in heavy-duty or dangerous tasks.**

I. Introduction

Since humanoid robots have a body structure similar to a human, recent research on humanoid robots aims at taking over of the heavy-duty or dangerous tasks by robots in the same environment where people work. In these situations, a humanoid robot is required to recognize the environment and tools which are designed for a human and complete target tasks compensating for disturbances during task execution. A locomotion system for a humanoid robot is one of the important elements of a humanoid robot to execute such tasks. It has to measure and adapt to the environment with task constraints, such as translation of the posture, limitation of the sight and slipperiness of the foot. The previous works on the locomotion system of a humanoid robot focused on improving capability for walking in complex environments, but it is necessary to improve adaptability to task constraints in order to achieve the complex tasks.

In this paper, we adopt the task of carrying heavy object in the construction site, as shown in Fig. 1. The proposed system enables a humanoid robot to compensate for the locomotion errors even in the situation where the sight of the robot is limited, such as a heavy-duty task, by memorizing

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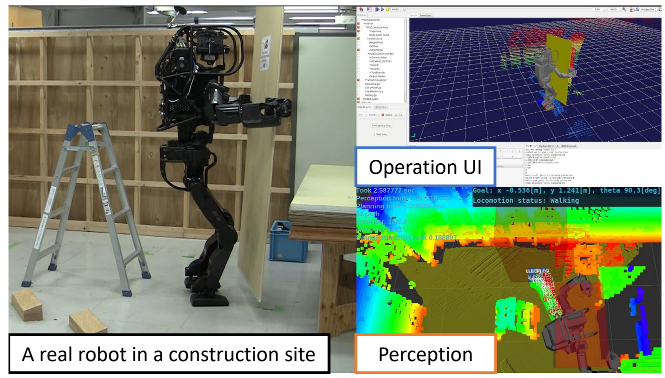

Fig. 1. A humanoid robot carries a 10kg panel in a construction site with task constraints. The whole-body motion for the task is generated and commanded by the user interface (upper right), and the robot autonomously plans and compensates footsteps avoiding occluded obstacles (lower right).

an environment as a smooth ground point cloud and a frequent obstacle point cloud. The major contribution of our paper is solving of the locomotion error problem due to the task constraints by compensating and re-planning footsteps based on these environmental memories. We also prove the practical feasibility of the proposed system by executing the heavy object carrying task in a construction site with a real humanoid robot, and improve locomotion accuracy while executing tasks by global footstep planning with these environmental memories and local footstep compensation based on the localization results.

II. Related Works

A. *Perception based locomotion system for a humanoid robot*

The construction method for a locomotion system of a humanoid robot is one of the major research topics in the field of robotics and many researchers have been developing environmental measurement systems, footstep planners and control strategies for biped walking in a complex environment. The currently mainstream method of locomotion planning is measuring the ground around its foot by external sensors and sequentially planning footsteps based on the measurement results. Nishiwaki et al. [1] proposed the locomotion system to traverse a rough terrain by generating a height map of the ground by a laser sensor attached on the torso of a humanoid robot and planning footsteps with it. Fallon et al. [2] achieved continuous walking on steps by generating a frequent point cloud of the ground by stereo fusion, which has an equivalent accuracy to laser scans. Karkowski et al. [3] proposed a fast online local footstep planning method with a grid height map based on a plane

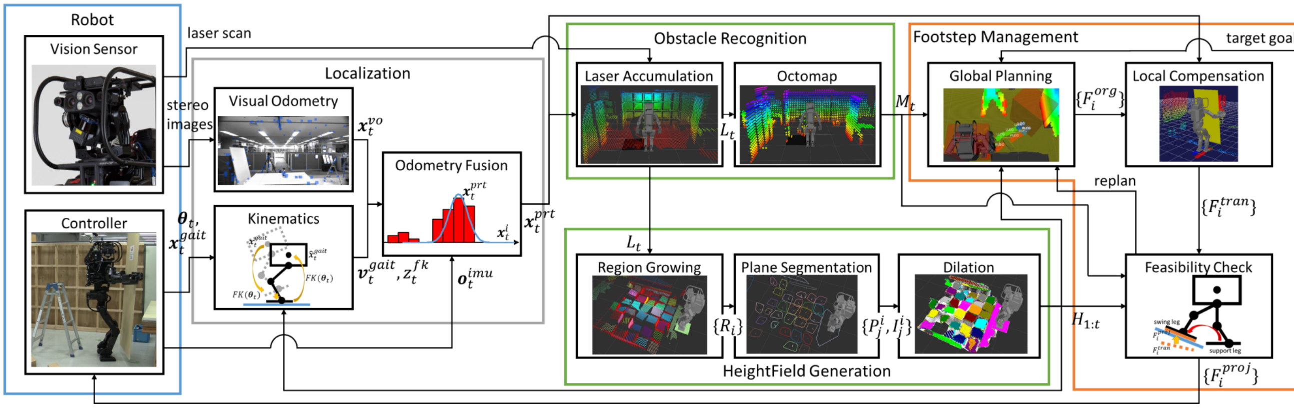

Fig. 2. Overview of proposed locomotion system

estimation and a local 2D path planning using a RGB-D camera. A sequential footstep planning method based on the environmental measurement is also applied to the locomotion planning with an obstacle avoidance. Maier et al. [4] proposed footstep planning method with a whole-body obstacle avoidance posture generation building height map using a RGB-D camera on the head of a robot. Hildebrandt et al. [5] proposed a gait trajectory generation strategy for the obstacle avoidance in real time by optimizing whole-body kinematics parameters These locomotion planning methods assume that the robot can measure the latest environments, especially the ground around its foot using the external sensors on it. However, when the robot executes some tasks like carrying a heavy object, the robot cannot always measure the latest ground around its foot due to the constraints of the task execution, such as occlusion by the object being carried and limitation of the viewpoint. In order to plan footsteps in such a situation, a robot needs to reuse the environmental point cloud measured in the past and plan footsteps globally. In such a system, it is necessary for the humanoid robot to accumulate environmental measurements as environmental memories and then localize itself accurately in it [6].

B. Footstep compensation for adaptive task execution

In the locomotion of a humanoid robot, it is difficult to achieve globally planned footsteps accurately by only using feedforward footstep placement because there are disturbances like model errors, slipperiness of its foot and environmental changes during locomotion. It is known that these disturbances have a significant effect on locomotion accuracy during tasks, especially which require the robot to carry heavy objects [7]. Therefore, it is important for a humanoid robot to compensate footsteps based on locomotion errors and determine footstep re-planing is needed or not, in order to achieve pre-planned locomotion for task execution. Oriolo et al. [8] proposed the feedback locomotion control, which enables a humanoid robot to trace a pre-planned target trajectory based on localization results. Garcia et al. [9] integrated visual servoing, which has been studied mainly in the manipulation field, and model predictive control in order to achieve dynamic walking control relative to the target object. However, it is necessary to estimate the landing state after compensation based on the measured environmental point cloud online because footsteps after compensation are not guaranteed to be feasible. Perrin et al. [10] proposed a fast obstacle avoidance strategy in planning footsteps by swept volume approximations and achieved footstep re-planning based on the obstacle models from motion capture device. Nevertheless, a locomotion system which enables a humanoid robot to compensate footsteps, estimate landing state and re-plan footsteps online based on the environmental measurement still remains a challenging problem.

C. Overview of the proposed approach

Based on the discussion, we propose a method of constructing the locomotion system for a humanoid robot which can accumulate environmental memories and compensate for locomotion errors under the task constraints. The overview of proposed system is shown in Fig. 2. The proposed locomotion system consists of three elements: localization, environmental memorization and footstep compensation. We adopt a particle filter based probabilistic localization method proposed by Kumagai et al. [11] for environmental memorization. We introduce a base link odometry compensation strategy based on forward kinematics and the ground measurements, which enables the localization system to fix the height errors caused by landing estimation of a stabilization controller. Next, we accumulate environmental measurements from laser scans based on the localization results and generate environmental memories for locomotion planning. We separate the environmental accumulation process into two parts: HeightField generation, which is highly accurate ground point cloud based on the plane segmentation and space interpolation, and octomap [12], which is suitable for frequent obstacle avoidance. Finally, we plan footsteps globally and compensate them locally based on the environmental memories and localization result. The proposed footstep planning system enables a humanoid robot to plan footsteps globally based on the environmental memories even in the situations where the robot cannot measure the ground around its foot directly. Then, we compensate these footsteps and determine the necessity of global footstep re-planning

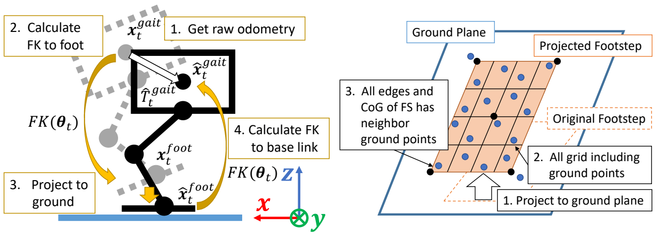

Fig. 3. Left: The base link odometry compensation based on the ground measurement, Right: Footstep projection to estimate landing state [14]

during locomotion based on the three landing elements: projectability, reachability and connectability.

III. Localization for Environmental Measurements

A. Fusion of Visual and Kinematics Odometry

In the localization part, we expand the particle filter based localization strategy proposed by Kumagai et al. [6], [11]. In this method, the probability distribution of the estimated pose is assumed to be the normal distribution $\boldsymbol{x}_t^{prt} \sim \mathcal{N}_t^{\boldsymbol{x}^{prt}}(\boldsymbol{x}; \boldsymbol{\mu}_t^{\boldsymbol{x}^{prt}}, \Sigma_t^{\boldsymbol{x}^{prt}})$. When the frequent target velocity distribution $\boldsymbol{v}_t^{gait} \sim \mathcal{N}_t^{\boldsymbol{v}^{gait}}(\boldsymbol{v}; \boldsymbol{\mu}_t^{\boldsymbol{v}^{gait}}, \Sigma_t^{\boldsymbol{v}^{gait}})$ is obtained from gait generator, the estimated pose distribution is updated analytically according to (1) and (2) based on the additivity of the normal distribution.

$$\boldsymbol{\mu}_{t+\Delta t}^{\boldsymbol{x}^{prt}} = \boldsymbol{\mu}_t^{\boldsymbol{x}^{prt}} + \boldsymbol{\mu}_t^{\boldsymbol{v}^{gait}} \Delta t \tag{1}$$

$$\Sigma_{t+\Delta t}^{\boldsymbol{x}^{prt}} = \Sigma_t^{\boldsymbol{x}^{prt}} + \Sigma_t^{\boldsymbol{v}^{gait}} \Delta t^2 \tag{2}$$

Then, we integrate 2D pose estimation $\boldsymbol{x}_t^{vo}$ from visual odometry [13], orientation around roll and pitch axis from an inertial measurement unit $\boldsymbol{o}_t^{imu}$ and base link height z_t^{fk} from kinematics calculation into the sampled particles from the pose distribution $\{\hat{\boldsymbol{x}}_t^i\} \leftarrow \mathcal{N}_t^{\boldsymbol{x}^{prt}}(\boldsymbol{x}; \boldsymbol{\mu}_t^{\boldsymbol{x}^{prt}}, \Sigma_t^{\boldsymbol{x}^{prt}})$. Because these measurement results have different dimensions, we calculate normalized weights w_t^i according to their reliability as (3) and apply resampling process to $\{\hat{\boldsymbol{x}}_t^i, w_t^i\}$.

$$w_t^i \sim p(\boldsymbol{z}_t|\hat{\boldsymbol{x}}_t^i) = p(\boldsymbol{x}_t^{vo}|\hat{\boldsymbol{x}}_t^i) p(z_t^{fk}|\hat{\boldsymbol{x}}_t^i) p(\boldsymbol{o}_t^{imu}|\hat{\boldsymbol{x}}_t^i) \tag{3}$$

This method can do both: reduce computational costs and estimate accurate 6D pose of a humanoid robot by extracting reliable parts from measurement resources and integrating them into weights. However, the base link height estimation based on the model based kinematics has the problem that estimation result tends to drift because of the model errors or wrong landing state estimation by the stabilization controller. This problem is especially remarkable in a locomotion during task execution, such as carrying a heavy object.

B. Kinematics Compensation with Ground Plane

In order to solve the drift problem caused by model errors and poor landing state estimation, we introduce a waist height compensation strategy based on both forward kinematics and environmental measurements. The overview of the proposed waist height compensation is shown on the left of Fig. 3. The method to generate ground point cloud is discussed in Subsection IV-A. We assume that at least one of the robot's foot is completely landed on the ground and calculate estimated posture of the support foot $\boldsymbol{x}_t^{foot}$ by solving a forward kinematics from base link posture from gait generator $\boldsymbol{x}_t^{gait}$ using joint angles $\boldsymbol{\theta}_t$. Then, we project $\boldsymbol{x}_t^{foot}$ vertically to the ground point cloud and obtain projected footstep posture $\hat{\boldsymbol{x}}_t^{foot}$. Finally, compensated base link posture $\hat{\boldsymbol{x}}_t^{gait}$ can be calculated by solving a forward kinematics from $\hat{\boldsymbol{x}}_t^{foot}$ using $\boldsymbol{\theta}_t$. When robot is in double support phase, we calculate midcoords of forward kinematics solutions from both projected support legs. We use the vertical height of compensated base link posture $\hat{\boldsymbol{x}}_t^{gait}$ as the measurement of the waist height z_t^{fk} for weighting explained in Subsection III-A.

In order to project a footstep to the ground point cloud, we adopt the landing state estimation method proposed by Ueda [14]. The overview of his method is shown on the right of Fig. 3. In this method, the ground point cloud is cropped around the target footsteps and local plane estimation is applied to them. Then, the target footstep is projected vertically to the estimated plane and points around the projected footstep are randomly sampled from ground point cloud. The projected footstep is divided into grids with a resolution of n_f and it is regarded to have been landed if all the grids include a sampled ground point and all edges and the center of gravity (CoG) of the footstep have a neighbor ground point. This projection method is also used in footstep planning and compensation discussed in Section V.

In the locomotion system of a humanoid robot, the assumption that at least one of the robot's foot is completely landed on the ground is not obvious because of the disturbances such as heel and toe contact, landing impact and slipperiness of the foot. This problem greatly affects the accuracy of the estimation, especially analytical estimation approaches such as Kalman Filters [15], [16]. On the other hand, the proposed system can solve this problem by adopting only reliable estimations because this estimation is used as measurement update in the Particle Filter. We determine that a base link estimation has enough reliability when the target foot is in a supporting phase of the generated gait trajectory and the norm of a force sensor attached on the support foot is larger than the pre-defined threshold. Especially, we do not project the target footstep when supporting foot is in heel landing or toe off phase, where the landing state of the support foot is not stable, and estimate $\hat{\boldsymbol{x}}_t^{gait}$ using the transformation matrix $\hat{T}_{t-1}^{gait}$ obtained by the previous compensation by (4) assuming that the variation of the waist error is small enough in one control cycle.

$$\hat{\boldsymbol{x}}_t^{gait} = \hat{T}_{t-1}^{gait} \boldsymbol{x}_t^{gait} \tag{4}$$

IV. Environmental Memorization

A. HeightField Generation for Ground Recognition

The ground point cloud, which is used in the base link compensation and landing state estimation discussed in Subsection III-B, requires high accuracy and density, whereas high frequency and processing speed are not always necessary because the ground would not change frequently. In this paper, we propose an accurate point cloud generation algorithm called HeightField, which achieves accurate and dense point cloud generation by plane estimation and space interpolation and hence, solves the problem of the laser point cloud being too sparse to execute landing state estimation. The algorithm to generate HeightField is shown in Alg. 1. HeightField $H_{1:t}$ is a 2.5D democratized grid map with height information on each grid. In this paper, we define the resolution of the HeightField as 0.01[m]. First, we extract the ground point cloud $\hat{L}_t$ which is in the range of dz from the foot of the robot from the laser point cloud L_t and perform clustering by applying region growing to it. Then, we perform plane estimation of each of the obtained cluster $\{R_i\}$ and extract the pair of the plane P^i_j and corresponding point set I^i_j in cluster R_i. We call this pair (P^i_j, I^i_j) as a Face. Next, we pick up each of the grid (x, y) belonging to the point set I^i_j and calculate the height of the grid h_p by projecting it to the plane P^i_j. We also update N neighbor grids around (x, y) using the plane P^i_j in the same way. The N neighbor set $Range(N)$ is the set of a grid (dx, dy) which satisfies $\|dx\| + \|dy\| < N$ and this process is equivalent to performing a dilation process using a kernel of size N on a 2D image which has height information in each pixel. In this paper, we provide the HeightField in 0.2Hz on average.

Algorithm 1 HeightField Generation

$H_{1:t} \leftarrow H_{1:t-1}$
$\hat{L}_t \leftarrow GroundPassThroughFilter(L_t, dz)$
$\{R_i\} \leftarrow RegionGrowing(\hat{L}_t)$
for $R_i \in \{R_i\}$ **do**
  while $R_i \neq \emptyset$ **do**
    $(P^i_j, I^i_j) \leftarrow PlaneSegmentation(R_i)$
    $\{(P^i_j, I^i_j)\} \leftarrow (P^i_j, I^i_j)$
    $R_i \leftarrow R_i \setminus I^i_j$
  end while
end for
for $(P^i_j, I^i_j) \in \{(P^i_j, I^i_j)\}$ **do**
  for $(x, y) \in I^i_j$ **do**
    for $(dx, dy) \in Range(N)$ **do**
      $h_p \leftarrow calculateHeight(x + dx, y + dy, P^i_j)$
      if $h_p > H_{1:t}(x + dx, y + dy)$ **then**
        $H_{1:t}(x + dx, y + dy) \leftarrow h_p$
      end if
    end for
  end for
end for
return $H_{1:t}$

B. Octomap for Frequent Obstacle Detection

In order to check collisions with the environment for each step during locomotion, frequency and processing speed are important for the obstacle point cloud. In this paper, we convert laser point cloud L_t into Octomap proposed by Hornung et al. [12] and accumulate it as an obstacle point cloud. Octomap generates environmental point cloud for detecting collision between robot and an environment, which is useful for us to avoid collisions in global footstep planning and local footstep compensation process during locomotion. We defined the frequency of this obstacle point cloud as 5.0Hz, which is the frequency sufficient to check collisions in the transition time of a step in walking (about 1sec).

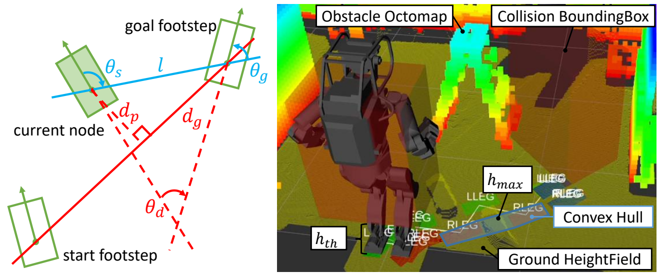

Fig. 4. Left: Parameters for heuristics functions: step cost heuristics proposed in [17] (blue) and additional cost for shortest path (red). These parameters are not negative. Right: Overview of obstacle avoidance strategy

V. Footstep Management

A. Global Footstep Planning

1) Heuristics function for more intuitive footsteps: For a global footstep planning, we use A* algorithm based footstep planning method proposed by Ueda et al. [17]. In order to plan footsteps by A* algorithm, we need to define foot placement candidates for next step, which is called a successor, and heuristics function adaptively [18]. In task execution, successors are defined depending on the target task because allowable foot placements will change according to tasks executed by the robot. Regarding to the heuristics function for a footstep planning, Ueda et al. [17] proposed cost function $h_s(n)$ for current footstep node n as (5). The parameters for $h_s(n)$ are shown in blue characters on the left of Fig. 4. l_{max} is the maximum translation amount and θ_{max} is the maximum rotation amount, which are defined by the successors according to the target task.

$$h_s(n) = \frac{l}{l_{max}} + \frac{\theta_s + \theta_g}{\theta_{max}} \tag{5}$$

This heuristics function $h_s(n)$ has an advantage in robustness for obstacle avoidance and planning speed, but has a problem that its solution is not always the shortest path as it is not admissible. Therefore, the solution of footstep planing based on $h_s(n)$ is sometimes not intuitive due to the strong assumption for its search path, especially when walking backward or sideways during the task execution. Then, we define the cost function $h_p(n)$ as (6), which means penalty to the distance from the ideal shortest path. The parameters for $h_p(n)$ are shown in red characters on the left of Fig. 4. This $h_p(n)$ consists of the cost function for trajectory tracking proposed by Chestnutt et al. [19] and the rotation term for target footstep.

$$h_p(n) = \frac{d_p + d_g}{l_{max}} + \frac{\theta_d}{\theta_{max}} \tag{6}$$

Though $h_p(n)$ is also not admissible, this heuristics function tends to provide footsteps which follow the shortest straight

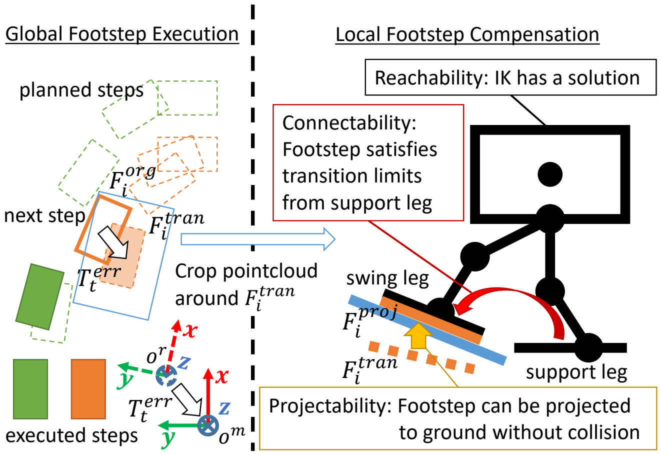

Fig. 5. Overview of footstep compensation

path. Therefore, we take a weighted average of $h_s(n)$ for robustness and $h_p(n)$ for intuitiveness as (7) with a weight parameter w.

$$h(n) = (1 - w)h_s(n) + wh_p(n) \tag{7}$$

2) Obstacle avoidance: In this paper, we divide the obstacle avoidance process into two parts: collision avoidance for upper body with obstacle point cloud and swing height calculation for stepping over obstacles with ground point cloud. The overview of obstacle avoidance planning is shown on the right of Fig. 4. First, we simplify the robot model to a rectangular bounding box for the collision avoidance planning for the upper body. Then the footstep candidates are rejected in the global footstep planning process when the obstacle point is inside of the bounding box [6], which enables a humanoid robot to avoid large obstacles while keeping the computational speed fast. The bounding box has an offset h_{th} from the ground to ignore small obstacles which a robot can step over. After the global footstep planning is solved, we extract ground points in a convex hull composed of the landing footsteps of each swing leg and calculate the highest ground height h_{max}. The swing height of the swing leg is defined as $h + h_{max}$ in order to step over small obstacles. h is a default swing height and set to 0.05m.

B. Environment Adaptive Footstep Compensation

In order to execute globally planned footsteps accurately, a humanoid robot has to compensate footsteps and estimate landing state online during locomotion. In this paper, we achieve footstep compensation and decision of re-planning online by integrating frequent localization and local foot placement search. Each step of the global footstep planning result $\{F_i^{org}\}$ is compensated and sent to footstep queue of gait controller sequentially, while keeping the length of the queue constant. The overview of footstep compensation method is shown in Fig. 5. We assume in the following explanation that robot coordinate o^r and localization coordinate o^m accord when the robot started to walk and the footsteps are represented in robot coordinate o^r, which is without loss of generality. The locomotion error at time t is obtained as the transformation matrix T_t^{err} from the origin of o^r to that of o^m. Then, we can calculate the correct footstep F_i^{tran} which is originally planned by global footstep planner regarded as the next target footstep F_i^{org} as (8).

$$F_i^{tran} = T_t^{err} F_i^{org} \tag{8}$$

However, F_i^{tran} is not always feasible because of the accumulated locomotion errors, change of the environment and kinematics constraints. Therefore, we clip the environmental memories around F_i^{tran} and obtain F_i^{proj} by projecting F_i^{tran} to the ground point cloud. Then, we determine the feasibility of F_i^{proj} by the following three landing elements: projectability, reachability and connectability. F_i^{proj} is regarded as appropriate footstep and sent to footstep queue if F_i^{proj} satisfies all three elements, otherwise the global footstep re-planning is required.

1) Projectability: Projectability means that F_i^{tran} can be projected to the ground plane as F_i^{proj} by the projection method explained in Subsection III-B and the collision bounding box put on the midcoords of F_i^{proj} and support foot do not collide with the obstacle point cloud. The collision detection method used in this process is the same as that of the global footstep planning in Subsection V-A.

2) Reachability: Reachability means that there is a solution of the whole-body inverse kinematics to reach the foot of swing leg to F_i^{proj} while fixing the support leg. This inverse kinematics calculation avoids self collisions of the robot model using PQP [20], but does not consider its swing trajectory. We put target CoG of whole-body inverse kinematics right above the support foot in the inverse kinematics calculation assuming that the dynamic gait trajectory is executable if static walking is feasible.

3) Connectability: Connectability means the relative transformation from the support leg to F_i^{proj} is within the pre-defined allowable range. The allowable range of the footstep is limited by the task constraints, such as the collision with the carrying object and limitation of the gait trajectory generation, even if F_i^{proj} satisfies the Reachability. This allowable range is a parameter for considering these task dependencies and defined as the same as the successors used in the global footstep planning.

VI. Experimental Evaluation

A. Experimental scenario

We conducted an experiment in which the humanoid robot HRP-5P carries a panel of dimensions 910mm×1820mm×10mm and about 10kg weight in a construction site. The scenario of the experiment is shown in Fig. 6. First, the robot has to step over two partition blocks, with sizes of 115mm×380mm×100mm (maximum height), to a work bench while accumulating environmental measurements. Next, the robot lifts up a panel and carried it to the wall while avoiding collision with occluded obstacles such as a ladder or a tool box. Finally, the robot places it down in front of the wall. The goal for each locomotion are directed by the operator, and the robot autonomously plans and compensates footsteps by the proposed framework.

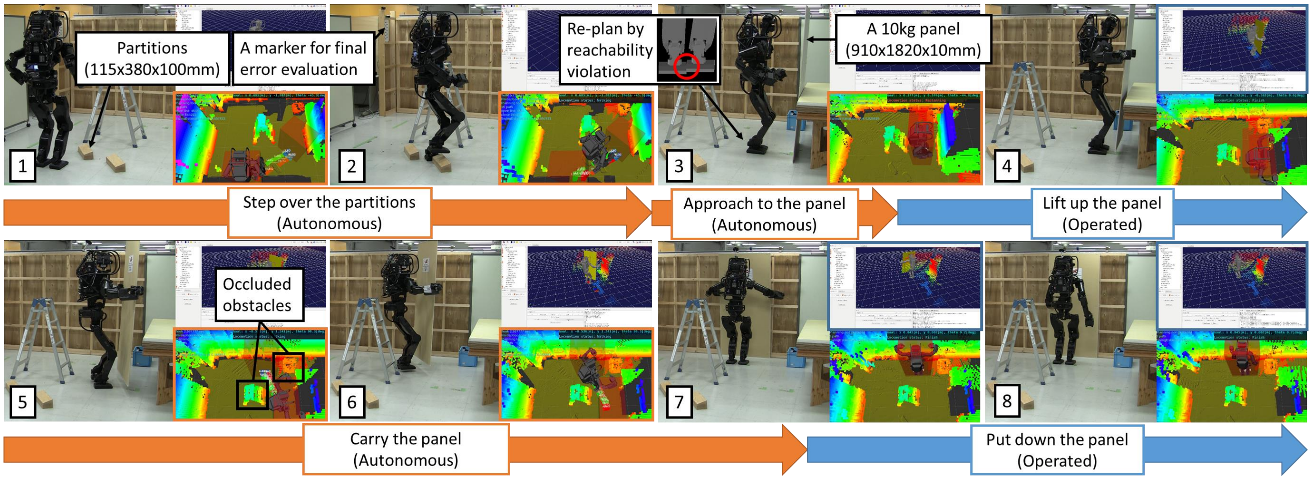

Fig. 6. The overview of carrying a construction panel experiment: The left is the conditions of a experiment, the upper right is the control interface and the lower right is a environmental memories and locomotion planning result. The robot autonomously stepped over the partitions in 1 to 2 and approached to the panel in 3. In this trial, the footstep re-planning was autonomously executed once while approaching to the panel in 3. Then, the robot lifted up a panel in 4 by the teleoperation and autonomously carried it in 5 to 6. Finally the robot put it down in 7 to 8 by the teleoperation.

When it assesses that the compensated footsteps are not feasible, it autonomously executes global footstep re-planning in order to reach the target position, and if the re-planning is failed, it stops the task for safety and waits for the operator's help. The whole-body motions of the robot for lifting up and putting down the panel are generated by the prioritized inverse kinematics [21] and sent to the robot using the user interface [22] by teleoperation. We introduce the online gait generator and stabilizer [23] in order to execute compensated footsteps sequentially. We use the weight parameter for footstep planning $w = 0.5$, the bounding box offset $h_{th} =$ 0.5m and the resolution of footstep projection $n_f = 6$ in stepping over the partitions, and $w = 0.8$, $h_{th} =$ 0.3m and $n_f = 3$ in carrying the panel.

B. Evaluation of locomotion accuracy

We evaluated the accuracy of the locomotion with the proposed localization and footstep management during the experiment of carrying a panel. The result is shown in Fig. 7. From these results, it can be confirmed that the locomotion errors of the gait generator is corrected by the visual odometry in the x and y translation and yaw rotation. The visual odometry and gait generator are both drifting in z translation, but localization result remains stable owing to the proposed base link height compensation. The orientation around the roll and pitch axis is estimated by the inertial measurement unit accurately, even though the visual odometry estimation suffers from large rotation errors. The evaluation result of the final errors in locomotion is shown in TABLE. I. We executed this experiment 4 times and averaged the final errors in locomotion obtained by the marker detection. It can be seen that the proposed method reduced about 50 $\sim$ 95 % of the errors of a raw gait generator estimation.

C. Evaluation of environmental memories

We evaluated the accuracy of the proposed HeightField during locomotion of the real robot in order to confirm its

TABLE I

THE FINAL ERRORS IN LOCOMOTION (AVG OF 4 TRIALS)

	x trans	y trans	yaw rot
Proposed system	0.031 m	0.074 m	-2.92 deg
Raw gait generator	0.595 m	-0.369 m	6.03 deg
Reduced abs errors	94.8 %	79.9 %	51.6 %

feasibility for locomotion planning. We estimated the ground plane from HeightField generated by the real robot during the carrying a panel experiment by RANSAC and calculated the distance from it to the ground points included in the estimated ground plane. The error histogram is shown on the left of Fig. 8. It can be confirmed that the majority of the points are almost in the range of $\pm$0.025m. The time series of the variance of ground points during locomotion is also shown on the right of Fig. 8. The worst variance was $0.000312\mathrm{m}^2$ and this value is small enough for the landing state estimation.

VII. CONCLUSION

In this paper, we proposed a construction method of a perception based locomotion system which enables a humanoid robot to achieve adaptive footstep management under the constraints for task execution. We applied the proposed system to a humanoid robot and proved its usefulness by successfully executing a heavy object carrying task. The proposed system solves the problems due to limited sight by integrating an accurate localization with ground measurement based waist height compensation, and environmental memorization which consists of the HeightField for ground plane estimation in $0.000312\mathrm{m}^2$ variance at worst and Octomap for frequent obstacle avoidance. Moreover, we enabled a humanoid robot to plan footsteps globally while taking account of the occluded environments using the environmental memories, and improved the locomotion accuracy by local footstep compensation while considering the landing state online. The proposed system reduced about 50 $\sim$ 95 % of the locomotion errors of a gait generator, even

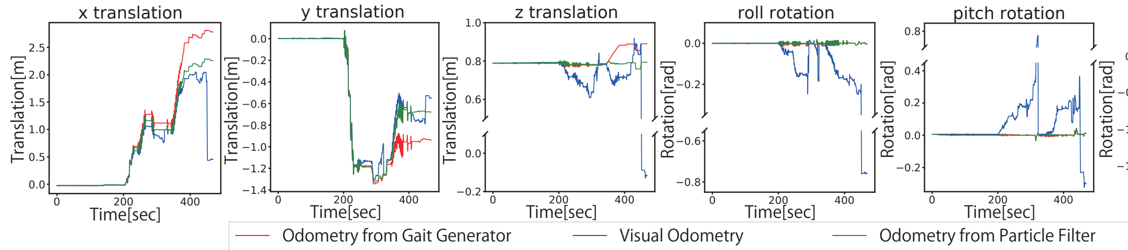

Fig. 7. The localization result of translation and rotation during carrying the panel. For z translation, roll rotation and pitch rotation graphs, breaks have been inserted in the y-axes range for better visualization as there are large drifts in visual odometry estimation caused by lifting up and putting down motion of the robot. The proposed localization can provide stable 6D pose estimation owing to the base link height compensation and orientation from the inertial measurement unit.

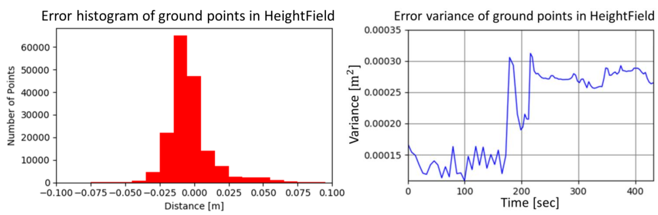

Fig. 8. The distance error histograms (left) and variance (right) of the ground points in HeightField in the carrying a panel experiment.

in the situation where the robot has a 10kg panel. From above results, we concluded that the proposed system contributes to improvement of locomotion abilities of a humanoid robot which engages in heavy-duty or dangerous tasks with the task constraints.

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