Course Detection from Integrated 3D Environment Measurement by Multiple Mobile Robots

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This paper describes a novel selection method of course direction for a mobile robot. We focus on the scene when a mobile robot cannot select an appropriate course direction by its own sensor information. The proposed method enables appropriate selection of course direction for a mobile robot by integrating measured data acquired by multiple mobile robots. Experimental result shows that the proposed method can decide appropriate course direction for a mobile robot.

1 Introduction

Mobile robots are becoming capable of dealing with complex environments. For most mobile robot operations in complex environments, such as disaster sites, navigation on rough terrain is one of the main problems. Various approaches about terrain traversability analysis (TTA) and navigation of mobile robots on rough terrain have been studied. Hata et al. proposed TTA method for outdoor mobile robot navigation using linear support vector machine [1]. In this method, support vector machine needs training data. The fact that the quality of training data affects accuracy of classification is well-known. Therefore, it is probably not possible of this method to classify terrain traversability with adequate quality under the existence of complex terrain because correct traversability labeling of complex terrain and generation of training data from these labeling result tend to be difficult. In order to overcome this shortcoming, the authors proposed a novel TTA method [2]. In this method, selection of course direction for a mobile robot is performed using measured data which is acquired from mobile robot's anterior region. Although this method realizes appropriate TTA of complex terrain without collection of training data, the sensing area for TTA task is restricted to mobile robot's nearest anterior region. These prerequisite conditions cause inadequate selection of course direction depending on the structure of terrain area. Figure 1 shows an example of the situation when a mobile robot cannot select appropriate course direction with the conventional TTA method. In Fig. 1, the slope area of mobile robot's anterior region is selected as the course direction toward the goal position. However, this selection is not adequate because the end edge of the slope is not-traversable. This kind of problem happens due to limited sensing area of mobile robot.

In this paper, we propose a novel approach for mobile robot's selection of course direction. To overcome the inadequate selection of course direction shown in Fig. 1, we adopt multiple mobile robot system. Our approach integrates TTA results generated by each robot independently, and outputs appropriate selection of course direction eventually.

2 Proposed method

In our method, mobile robot's selection of course direction is performed based on the vector field histogram (VFH) [3].

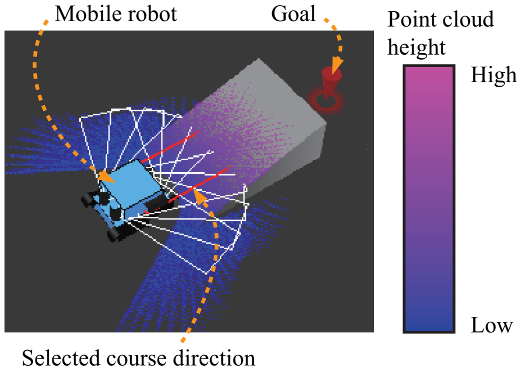

Fig. 1 Scene example of inadequate selection of course direction.

VFH expresses traversability of mobile robot's surrounding area and mobile robot selects traversable direction in VFH as its course direction. Our method is composed of two steps. First step is VFH generation with conventional methodology, second step is VFH integration.

2.1 Initial VFH generation

First, each mobile robot generates VFH independently. The methodology of initial VFH generation comes from the conventional method [2]. Here, mobile robot collects point cloud data about their surrounding environment and these measured data are used for TTA and VFH generation.

2.2 VFH integration

In our method, each mobile robot sends VFH to the environment server and the environment server plays VFH integration role. VFH integration is based on weighting of risk value and risk value updating. Under the circumstance such as using two mobile robots, the environment server receives two VFHs. Figure 2 shows data processing flow in this configuration. Specifically, mobile robot A sends $\mathrm{VFH_A}$ and mobile robot B sends $\mathrm{VFH_B}$ to the environment server. For mobile robot A's appropriate selection of course direction,

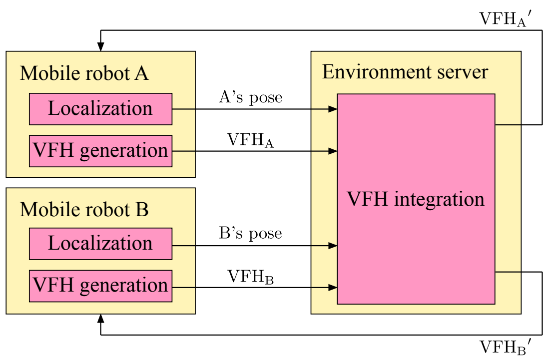

Fig. 2 Illustration of data processing flow.

the environment server weights $\mathrm{VFH_B}$ and integrates it with $\mathrm{VFH_A}$. The final output is $\mathrm{VFH_A'}$ and it is sent to mobile robot A. The weighting procedure is as follows:

$$w = \begin{cases} -\frac{1}{L_{\mathrm{th}}}(L_{\mathrm{AB}} - L_{\mathrm{th}}) & (0 \leq L_{\mathrm{AB}} \leq L_{\mathrm{th}}) \\ 0 & (otherwise) \end{cases}, \quad (1)$$

$$\forall_{\phi \in \text{Measured direction set in } \mathrm{VFH_B}}, \; r_\phi^{\mathrm{B}\prime} = w r_\phi^{\mathrm{B}}, \quad (2)$$

Here, w is the weight, L_{th} is the distance threshold which controls weighting, L_{AB} is the Euclidean distance between mobile robot A and mobile robot B, and r_ϕ^{B} are risk values in $\mathrm{VFH_B}$. Weighted risk value $r_\phi^{\mathrm{B}\prime}$ is calculated as the product of w and r_ϕ^{B}.

Risk value updating is executed based on differences of mobile robots' relative attitude α which is measured in degree unit. Risk values r_ϕ^{A} in $\mathrm{VFH_A}$ which satisfy specific conditions for updating are replaced by risk value $r_{\mathrm{max}}^{\mathrm{B}}$. $r_{\mathrm{max}}^{\mathrm{B}}$ is the value found among $r_\phi^{\mathrm{B}\prime}$ which exist in weighted $\mathrm{VFH_B}$. After updating risk value of $\mathrm{VFH_A}$, $\mathrm{VFH_A}'$ is generated and sent to the mobile robot A from the environment server.

3 Experimental result

To test our method, we had an experiment with the environment shown in Fig. 1. In the experiment, we assumed that there were two exactly same mobile robot and their TTA results were integrated in the environment server. These mobile robots and environment server were implemented virtually on the simulator. The values of each parameter were as follows: $L_{\mathrm{th}} = 20$ m, $r_{\mathrm{limit}} = 70$. Risk value threshold r_{limit} is the value proposed in conventional method [2]. In our experiment, $\mathrm{VFH_A}$ and $\mathrm{VFH_B}$ were integrated in the virtual environment server. By integrating two VFHs, $\mathrm{VFH_A'}$ which enabled appropriate selection of course direction for mobile robot A was output.

Figure 3 shows two mobile robots in the experimental environment and mobile robot A's selection of course direction. In the experiment, calculated parameters' values were as follows: $L_{\mathrm{AB}} = 2.06$ m, $w = 0.897$, $\alpha = -60.9$ degree. VFHs generated by two mobile robots independently and integrated $\mathrm{VFH_A'}$ are shown in Fig. 4. Based on the integrated $\mathrm{VFH_A'}$, mobile robot A selected appropriate course direction toward the goal position shown as red rectangular in Fig. 3 and 4 (c). This selection is different from the inadequate one shown in Fig. 1. Consequently, the proposed method made it possible for mobile robot A to select appropriate course direction.

4 Conclusion

In this paper, we proposed a novel approach for mobile robot's selection of course direction. Our approach is based on multiple mobile robot system. The proposed method enables a mobile robot to select appropriate course direction under specific situation using integrated VFH information generated by multiple mobile robots.

Experimental result showed that the mobile robot could select appropriate course direction by our proposed method. These results were achieved under the situation when a mobile robot could not select appropriate course direction by its own sensor information only. Integration of multiple mobile robots' measured data could generate VFH which had appropriate risk values for a selection of course direction.

Future work will involve validation of the proposed method with real multiple mobile robots. Furthermore, extension of the proposed method for different types of mobile robots is also needed.

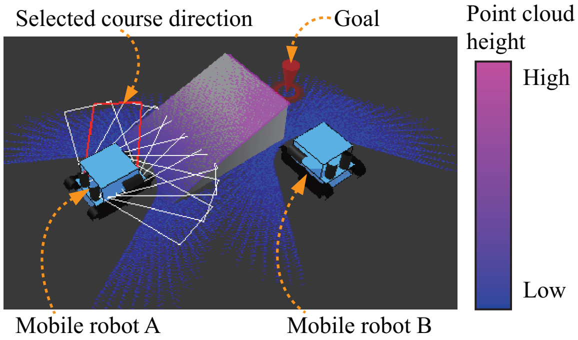

Fig. 3 Experimental result on the simulator.

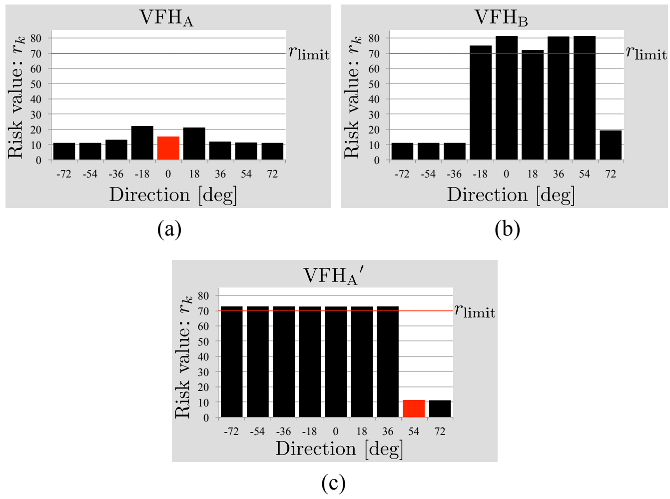

Fig. 4 Generated VFHs: (a) VFH from mobile robot A's measurement, (b) VFH from mobile robot B's measurement, (c) integrated VFH.

Acknowledgement

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References

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