Docking Performance Against Turbidity Using Active Marker Under Day and Night Environment

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Abstract: Nowadays, Autonomous Underwater Vehicle (AUV) is playing an important role for human society in different applications such as inspection of underwater structures (dams, bridges). We have developed a stereo-vision based docking approach for underwater battery recharging to enable the AUV to operate for extended periods without returning surface vehicle for recharging. Since underwater battery recharging units are supposed to be installed in deep sea, the deep-sea docking experiments cannot avoid turbidity and low light environment. In this study, the proposed system with a newly designed an active 3D marker have been developed to improve the performance of the proposed system especially in turbid water. We conducted experiments to verify the robustness of the proposed docking approach in a simulated pool where lighting changes from day to night and the water is turbid. The experimental results have confirmed the robustness of the proposed docking system against turbidity and illumination variation.

Keywords: Visual Servoing, active marker, underwater docking, stereo vision, turbidity, illumination variation

1 INTRODUCTION

Japan has many areas of sea from which future resources can be taken out using advanced technologies. Autonomous Underwater Vehicle (AUV) plays an important role in deep sea works such as oil pipe inspection, survey of sea floor, searching expensive metal, etc [1]-[4]. Japan government is now seriously considering searching methane hydrate as future energy solution. To do such novel works that takes long period in deep sea, one of the main limitation of AUVs is limited power capacity. To solve this problem, underwater battery recharging unit with a docking function is one of the solutions to extend the operation time of AUVs. Several approaches using different sensors have been conducted worldwide for underwater docking operation [5]-[6]. Normally, long navigation is performed using acoustic sensors and camera vision is used for final step of docking process. Vision-based navigation is one of the dominant positioning units especially high accuracy is essential. Vision based system can be integrated with other sensor units.

Most of the studies related to vision based navigation for underwater vehicle are based on single camera [7]-[9]. Apart from them, we have developed a stereo-vision based docking approach for AUV [10]-[13]. In our approach, the relative pose between the underwater vehicle and a known 3D marker is estimated using Real-time Multi-step GA (RM-GA) that is real-time 3D pose estimation method. Avoiding the disadvantages of features based recognition methods that are based on 2D to 3D reconstruction, 3D model based matching method is used that is based on 3D to 2D projection method in our approach. One of the main drawbacks of 2D-to-3D reconstruction is incorrectly mapping between corresponding points in images.

Since underwater environment is more complex than space and ground, there are many disturbances for vision-based underwater vehicles. Therefore, it is important to consider the possible disturbances before testing the proposed approach in the sea. The common disturbances for vision-based underwater vehicle are light environment and turbidity. Since underwater battery recharging units are supposed to be installed in deep sea to save the time consuming and work done from human beings in the case of returning surface vehicle for recharging, the deep-sea docking experiments cannot avoid turbidity and low light environment. According to the authors’ knowledge, there is no study on docking system using stereo-vision based real-time visual servoing with performance tolerance of illumination and turbidity.

In this study, we newly designed an active 3D marker and used to improve the performance of the system especially in high turbidity. We conducted experiments to verify the robustness of the proposed docking approach in simulated pool where lighting changes from day to night and the turbidity of the water is high. The experimental results have confirmed the robustness of the docking system using stereo-vision based 3D pose estimation against turbidity and light changing.

The remainder of the paper is organized as follows: Section 2 describes the method of 3D pose estimation. Experiment results are reported in section 3 with discussion and conclude in section 4.
2 REMOTELY OPERATED VEHICLE

Hovering type underwater vehicle (manufactured by Kowa cooperation) is used as a test bed as shown in Fig.1. Two fixed cameras installed at the front of the vehicle are used for real time pose tracking. In thruster unit, four thrusters with maximum thrust force of 4.9[N] each are controlled to move the vehicle along desired path. The vehicle can dive up to 50 [m] and two LED light sources are also installed on the vehicle.

3 3D MOVING ON SENSING (MOS) USING REAL-TIME MULTI-STEP GA

In previous study [10], we introduced 3D MoS that uses three dimensional measurement with solid object recognition based on visual servoing technology. In this system, RM-GA is used to estimate the relative pose between the vehicle and a known 3D marker. Here, we will discuss on 3D pose estimation using RM-GA briefly for background of readers.

Figure 2 shows the model-based matching method using dual-eye cameras for 3D pose estimation. In Fig. 2, $\Sigma_{CR}$ and $\Sigma_{CL}$ are the reference coordinate frame of the right camera and the left camera. $\Sigma_H$ is the reference frame of the ROV. $\Sigma_M$ is the reference frame of the real target object. The solid model of the real target object in space is projected naturally to the dual-eyes cameras images and the dotted 3D marker model, where the pose is given by one of GA’s genes, is projected from 3D to 2D. The different relative pose is calculated by comparing the projected 2D image and the solid model captured by the dualeye cameras. Finally, the best model of the target object that represents the true pose can be obtained based on its highest fitness value. The fitness function is constructed to evaluate the matching degree between the projected model and the captured image. Detailed explanation about the fitness function is referred to our previous paper [14].

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3.3 Active Marker

In our previous researches [10]-[13], the passive marker was used to conduct the experiment. In the present study, the gain coefficient is adjusted to perform the best condition for \( v \) as the value of \( \epsilon \) is the rotation direction around the z-axis and it is expressed as the value of \( v_2 \). According to the experimental result, the gain coefficient is adjusted to perform the best condition for visual servoing.

4 EXPERIMENTAL RESULTS AND DISCUSSION

4.1 3D Pose Estimation in Turbid Water

The 3D pose estimation was performed when the ROV and 3D marker were fixed with a distance of 600 mm between them under different turbidity levels in day and night time. The amount of turbidity is controlled by adding mud in water in the tank. Mud is chosen in order to simulate the natural condition. In this experiment, the turbidity level (Formazin Turbidity Unit, FTU) is measured by using a portable turbidity monitoring sensor (Model: TD-M500, manufactured by OPTEX).

The ROV performed visual servoing at about 600 mm in docking operation. It is the aware distance for docking operation to recognize the target object. Therefore, we give prominence to discuss 600 mm distance for recognition performance. Figure 6 shows the fitness value against turbidity using mud and the ROV and the 3D marker were fixed in distance 600 mm. The horizontal axis is described by the amount of mud \((ml/m^3)\) and the vertical axis is expressed in terms of fitness values and FTU values.

According to the results, the fitness value decreases from 1.3 to 0.1 in the case of day time and from 0.6 to 0.1 in the...
4.2 Docking Performance Against Turbidity Under Changing Lighting Condition

This experiment was conducted in an indoor pool as shown in Fig. 8 in which the turbidity was created by adding mud (40 FTU). The desired pose \((x_d = 600 \text{ mm}, y_d = 15 \text{ mm}, z_d = -20 \text{ mm}, \) and \(\epsilon_d = \)...
of the active marker recognized by RM-GA. Figure 11 (d) indicates the trajectory of the underwater robot based on ΣII in Fig. 9 during the docking process.

In docking strategy, visual servoing starts when the 3D marker is detected, which means the fitness value is above a defined threshold (0.4 in the present study). When the pose of the vehicle is within the allowable error range of ±40 mm of the desired pose, as shown in Figs. 11(b), (c), and (e), and the orientation around the z-axis (f) is controlled to within 7 deg for the desired period (165 ms, which is equal to five times the control loop period) in this experiment, docking starts by decreasing the distance between the ROV and the 3D marker from 550 mm to 350 mm, as shown in Fig. 11(b). The dotted line labeled “A” in each subfigure of Fig. 11 indicates the visual servoing state, where the desired position along the x-axis is 600 mm, and the desired position along the y-axis is within the allowance error range, as shown in Fig. 11(c). Visual servoing continues until the desired pose is within the error range for the y and z directions and the orientation around the z-axis, as shown in Figs. 11(c), (e), and (f). At time “B”, as shown in Figs. 11(b), (c), and (d), the docking criteria are satisfied and docking operation starts. Note that the position in the x direction at point “B” is approximately 500 mm because only the positions in the y and z directions and the orientation around the z-axis are considered in the docking criteria. The docking operation started approximately 7 s after starting the experiment. Finally, the docking operation was successfully completed approximately 20 s after starting the experiment. The dotted line labeled “C” in each subfigure of Fig. 11 indicates the state whereby the docking is completed.

In the case of 80 Lx (night time), the fitness value is about 0.8 in recognition of active 3D marker at the start of the experiment and then decreased to about 0.5 as shown in Fig. 12(a). The ROV could recognize the active marker even though the environment is dark. The desired position along the orientation around the z-axis are out of error range at 3 s as shown in Fig. 12(f). Therefore, visual servoing continues.
until the desired pose of other direction y, z, and orientation around the z-axis is within allowance error range. The time for docking from the start of the experiment is 25 s in this case. The underwater robot was confirmed to maintain the desired pose while docking was performed under changing lighting condition at high turbidity, as shown in Figs. 11 and 12(a) through (f). According to the experimental results, even though the lighting condition was changed from day to night in high turbidity, the relative pose of the 3D marker can keep recognize well and the docking has been done successfully against turbidity under changing lighting condition.

5 CONCLUSION

This paper presents the docking performance against turbidity of the proposed dual-eye based docking system using an active 3D marker under changing lighting condition. Pool docking experiment was conducted against turbidity using an ROV. Turbid water was simulated using mud taken from the real sea. Recognition performance against turbidity under day and night was verified in terms of fitness value that is used in the 3D pose estimation of RM-GA. 17 times continuously repeated docking in the turbid water was conducted and docking performance under day and night environment was discussed in details. The experimental results have confirmed the docking performance of the proposed system against turbidity under different lighting conditions. Docking experiment in the turbid sea under day and night environment will be conducted in future.

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REFERENCES


