Visual-based Deep Sea Docking Simulation of Underwater Vehicle Using Dual-eyes Cameras with Lighting Adaptation

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***Abstract*—This paper proposes visual-based underwater vehicle docking/homing system under the environment especially simulated for deep sea trial. Instead of measuring absolute position of vehicle using other non-contact sensors, estimation of the robot's relative position and posture (pose) using dual-eyes cameras and 3D target object is proposed. For relative pose estimation, 3D model-based recognition approach is applied because of its real-time effective performance. According to effectiveness, simplicity and repeatable evaluation ability for real-time performance, Genetic Algorithm (GA) is utilized here as a modified form of " Multi-step GA" to evaluate the gene candidates that represent relative poses until getting the best gene with the most trustful pose in dynamic images input by videorate. P controller is used to control the vehicle for the desired pose using real-time images from dual-eyes cameras. Since the underwater environment is complex, this work also addresses to the experiment for deep sea docking operation under changeable lighting environment derived from pose fluctuation of underwater vehicle with two LED-lighting direction altered accordingly that offers huge challenges for visual servoing. As the main contribution for this paper, therefore, we have developed visual servoing using adaptive system for unknown lighting environment. Remotely Operated Vehicle (ROV) is used as a test bed and the experiments are conducted in simulated indoor pool. Experimental results show visual servoing performance under varying lighting conditions and docking performance using proposed system.**

I. Introduction

Nowadays, docking operation is standing as a critical challenge for autonomous underwater vehicles with such applications as sleeping under mother ship, recharging batteries, transferring data and new mission uploading. Research on the docking system using various homing sensors [1]-[3] and techniques [4]-[6] for the underwater robot has been conducted worldwide. Even though expensive navigation sensor suit and large scale dead reckoning sensors are able to provide accurate position data, the final approach of docking process especially for unidirectional docking station is still a difficult task. To achieve this task, visual-based docking system have been reported with the rapid progresses in computer vision technology recently. Some works are based on one camera [7]-[10] and some researches are implemented using two cameras. Even though two cameras are used in [11] [12], stereo vision that means seeing the same object at the same time by both two cameras has not been applied, meaning one camera is used for pose estimation and the other for another tasks. In contract, we have developed visual-based docking system for underwater vehicle using stereo vision. To the best knowledge of author, our proposed system is the first initiated research using stereo vision in underwater vehicle environment. What we have confirmed in [13] is that the docking process using proposed system has high homing accuracy. Even though the robustness of the proposed system against different kinds of disturbances was confirmed in previous work [14], we have not confirmed the robustness of the proposed system against the effect of the illumination variation under arbitrary light condition. In underwater vehicle system with lighting unit installed on it, especially, dynamic lighting environment addresses challenges when the own lighting system is dominant in deep sea or during night operation. According to disturbances such as water current, the resulting pose fluctuation will increase illumination variation and consequently the poor target recognition accuracy will make pose fluctuation larger and larger. Finally visual servoing may become out of controlling. Therefore, illumination variation is one of the challenging problems to be solved for robust recognition systems in unknown environment. Illumination variation increases with the illumination intensity and direction according to the number of illumination sources, type of illumination sources (normally assumed as the white source), static or dynamic position of each (robot, target and illumination sources) and types of environment that may introduce reflection and refraction issues. To achieve docking process with adaptability to illumination variation,

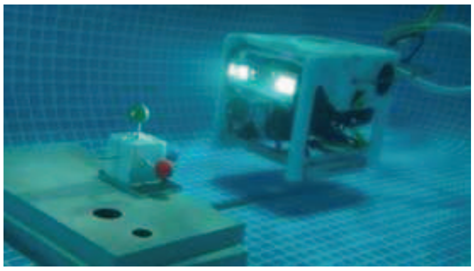

Fig. 1. Visual Servoing using 3D Maker and Dual-eyes Cameras

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therefore, we have developed visual based light adaptation system tolerable dynamic light environment variation.

A variety of approaches has been proposed to solve issues related to illumination variation. Most of them are to match the target object such as face between different images. According to literature, the methods used to solve the problems caused by illumination variation can be roughly classified into three categories: (1) recognition using training data set[15], (2) invariant feature extraction[16] and (3) pre-processing and normalization[17]. In recognition approach using training images, different number of training images of object under different light conditions are collected and used for recognition. Therefore, it addresses limitation for real-time application. Some approaches are based on the features that are invariant to light intensity variation. But their drawbacks occur significantly with the direction of illumination. Assumption of uniform illumination variation in pre-processing and normalization approach addresses poor performance in real environment. In most of the approaches for recognition under varying light conditions, illumination variation only due to different intensity is considered. Even though some approaches are with consideration of variation due to illumination direction, the position of illumination source is known and neither of camera nor object is dynamically moving in most cases. In this paper, therefore, we propose a robust 3D recognition method for docking application under arbitrary light condition in term of illumination intensity and direction.

This paper is organized as follows: Section II presents the proposed docking system for underwater vehicle. Section III describes proposed lighting adaptation system. Experimental results to assess the performance of the proposed system are described in Section IV with discussion. The final section concludes the paper.

II. Proposed Docking System

A. Docking Strategy

The proposed docking strategy consists of three steps: first, the ROV has to approach close to the 3D target till the target is in the field of view; second, detecting the object and regulating the vehicle to the defined relative pose of target is done in visual servoing step; and finally the third step in which the docking operation is completed. The flowchart of docking strategy is shown in Fig.2. The first approaching step can be extended for real world application using long distance navigation sensor such as GPS to navigate the vehicle into the visual range. However, the main contribution in this paper is focused on the second phase mainly and the third one to demonstrate the effectiveness of the proposed docking system. In visual servoing step, the vehicle is navigated and controlled to keep regulation with defined pose of target. In docking step, when the vehicle is stable with tolerance of position error in image plane (x,y) meaning fixed yawing and pitching for defined time period, forward thrust that makes the rode to fit into the dock is generated decreasing distance between the vehicle and target object gradually. Since the vehicle is hovering type, switching between visual servoing and docking mode using continuous pose feedback following docking strategy makes the system robust without surfacing hardly the docking station and minimizing the mechanical means as well.

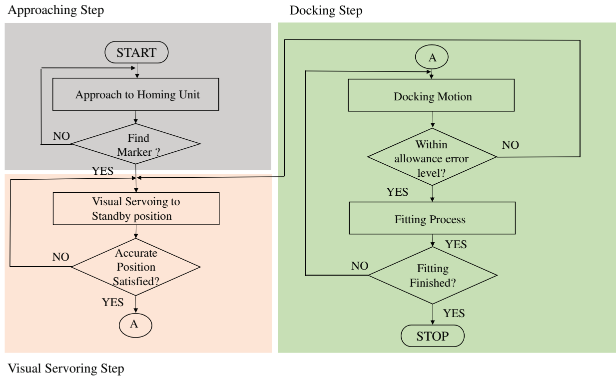

Fig. 2. Flowchart of Docking Strategy

B. Visual Servoing System using Stereo Vision

Fig.3 shows the overall block diagram of the proposed vision-based control system. The desired pose of the ROV related to the target is predefined. The relative pose of ROV with respect to known object is feedbacked to the P controller to compensate the error in pose. Estimation of relative pose is done by using model-based matching method. Model-based recognition approach is applied because of its real-time performance, comparing to other methods like feature based recognition in which the pose of the target object should be determined by a set of image points, resulting in complex searching the corresponding points and time consuming.

The control parameters for the ROV are x_d[mm], y_d[mm], z_d[mm] and ϵ_{2d}[deg]. The control algorithm is implemented in PC whose performance enables the real time pose tracking and visual servoing. The image signal and control signal are transferred through flexible cable with less influence to visual servoing due to less cable tension.

C. Model-based Matching using Multi-Step GA

Apart from other recognition methods based on 2D to 3D reconstruction, the proposed 3D model-based recognition is based on 3D to 2D projection. Moreover, the concept based on the group of pixels rather than individual pixels highlights merits of model-based method over feature-based ones. Pose of target object is estimated using model-based matching based on known 3D model of the target projected to 2D images. Target object is the 3D marker that consists of three spheres (40[mm] in diameter) whose colors are red, green and blue. Knowing the information of the target and predefined relative pose to the ROV, the solid model of the target is predefined and projected to 2D images. Comparing the projected solid model image with the captured 2D images by dual cameras, the relative pose difference is calculated. Fig.4 shows Model-based matching system using dual-eyes vision system.

Genes representative to six pose parameters as shown in Fig. 5 are initiated randomly. We have confirmed the gene that has the highest fitness function value represents the pose of the real target.Therefore the problem of pose recognition addresses to the searching problem. The solution is GA with promising speed and accuracy of performance. According to the performance in time-domain, GA is selected in this work even though there are advanced optimized techniques. The

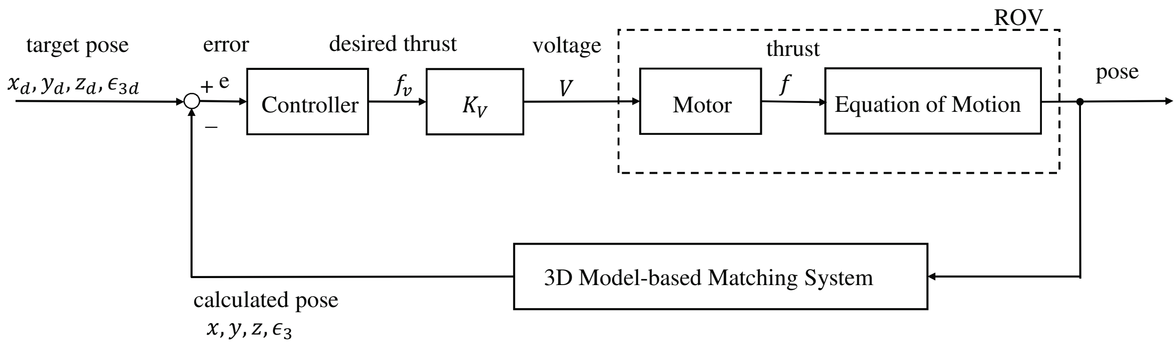

Fig. 3. Block Diagram of the Vision-based Control System

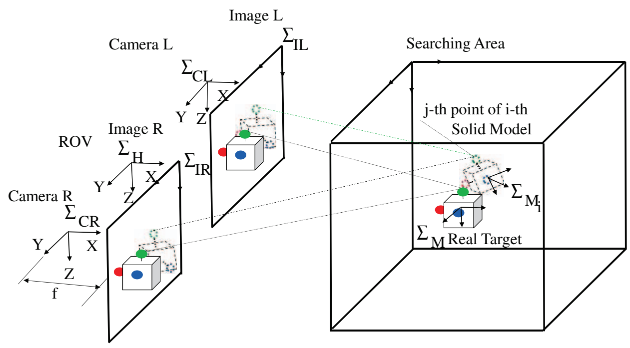

Fig. 4. Model-based Matching System using Dual-eyes Vision System

effectiveness of 1-step GA was confirmed in robots especially manipulators and reported in previous work [18]-[23]. The stability of the system was also confirmed by means of Lyapunouv analysis in previous work[21]. Through the steps of GA (Selection, Cross over and Mutation), a number of genes that represent different poses are evaluated by the defined fitness function to get the best gene with the most truthful estimated pose. A correction function representing a matching degree of projected model against the real target in the image, which is a correction function of real target projected in camera images with the assumed model represented by poses in genes, is used as a fitness function in GA process. The convergence of GA is realized in the sequences of dynamic images input by video rate [30 frames/s]. Detail discussion about 1-Step

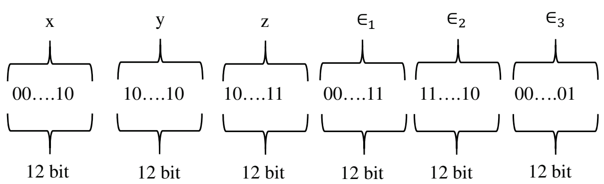

Fig. 5. Gene Representation for Position and Orientation

GA and fitness function are explained in [19]. The number of evolving generations in this experiment is 9 per 33 [ms] and the number of genes is 60.

D. Controller

Proportional controller is considered as the main compensator of the error between target's pose and recognized one. The control voltages of four thrusters are calculated by the

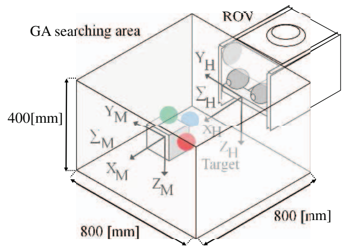

Fig. 6. GA Searching Area

following proportional control laws.

$$v_1 = k_{p1}(x_d - x) + 2.5 \quad (1)$$
$$v_2 = k_{p2}(\epsilon_{3d} - \epsilon_3) + 2.5 \quad (2)$$
$$v_3 = k_{p3}(y_d - y) + 2.5 \quad (3)$$
$$v_4 = k_{p4}(z_d - z) + 2.5 \quad (4)$$

where x_d, y_d, ϵ_{3d} and z_d are desired relative value based on Σ_H against 3D marker (see Fig.6), and v_1, v_3 and v_4 are the voltages for thrust of x-axis, y-axis and z-axis direction respectively. v_2 means the voltage for torque around z-axis. According to the thruster characteristics which is configured to stop for 2.5 voltage, the output voltages for thrust is the differentiated value gained by proportional gain value and added by offset value, 2.5. Based on experimental results, gain coefficients are tuned to have better performance in virtual servoing.

E. ROV as a Test-bed

The ROV shown in Fig. 7 manufactured by Kowa corporation, is used as the main test-bed for the proposed experiment. Two front fixed cameras (binocular camera) and four thrusters (traverse, horizontal and vertical direction) installed in the ROV are used for experiments. The specification of ROV is given in TABLE.I.

TABLE I. KEY FEATURES OF ROV

Dimension [mm]	280 (W) × 380 (L) × 310 (H)
Dry weight [kg]	15
Number of cameras	2 (Front, fixed) and 2 (Downward, fixed), 1 (Tile, Manual controlled)
Maximum thrust force [N]	9.8 (Horizontal), 4.9 (Vertical, Traverse)
Number of LED light Sources	2 (5.8 [W])

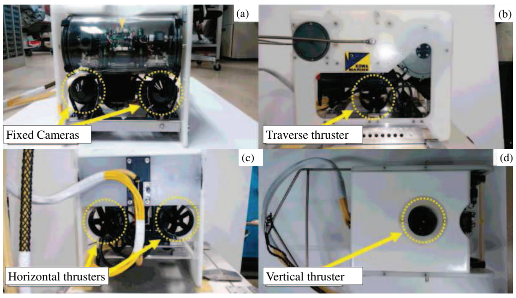

Fig. 7. Overview of ROV (a)Front view (b)Side view (c)Back view (d)Top view

III. Proposed Lighting Adaptation System

In this system, there are two illumination sources: natural source and robot's own LED source as shown in Fig.8. Since LED lighting source is installed on vehicle, it provides dynamic lighting environment with the motion of vehicle especially when LED light is dominant in deep sea. On the other hand, natural illumination source provides additional issues to illumination variation even though it can be considered as static and white source.

As discussed in section I, illumination compensation in recognition are generally based on preprossing such as filtering, modeling the light source and Global normalization. Apart from them, the proposed approach is based on the idea that is the information about changing appearance of object in images due to dynamic lighting can be obtained from sequential images captured in real-time. As shown in Fig.9, the histogram of basic color object under varying light condition can be seen as updating new one. For example, the solid histogram for three color objects is under one light condition and the doted histogram is under another light condition. Therefore, to detect the object under changing light condition is to detect the new histogram that looks like active one with respect to dynamic light environment. In proposed system, detection of 3D maker, that consists of three basic color balls, in 3D model-based recognition is based on thresholding in color space. Therefore, the issues to detect new histogram with respect to varying light is simplified to just detect the object with new range for each color object in color space. Therefore, selection of color space for detecting object and updating the range in selected color space for next recognition are considered as key points to reduce the effect of illumination variation on proposed recognition.

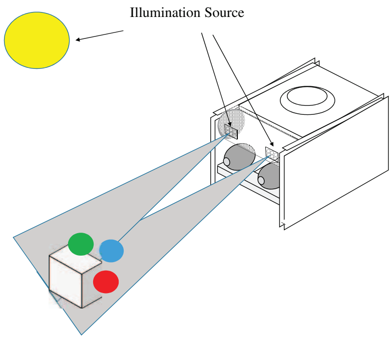

Fig. 8. Illumination Sources

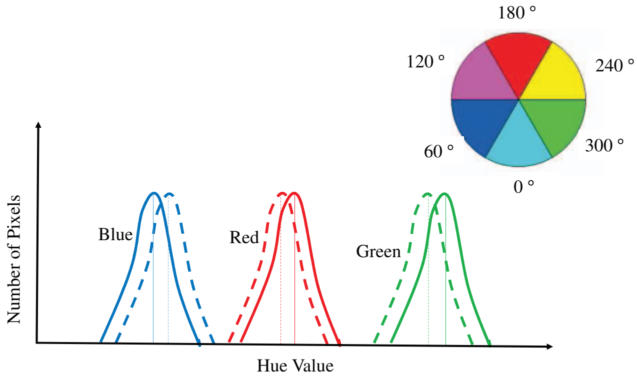

Fig. 9. RGB object in hue space

1) Selection of Color Space: Instead of using RGB space in recognition, color images are converted to HSV image. Among three parameters, hue is used as the main space because it is less affected by change of illumination brightness and direction. Again, due to the distance in degree in hue space as shown in Fig.9, three basic colors (blue, red and green) are selected for 3D marker.

2) Updating hue range: Although recognition using hue value is less sensitive to the illumination variation, it is needed to modify the recognition system to make as less sensitive to varying light condition as possible. Since detection of basic color object is done by thresholding in hue value, the process to detect object under changing light environment is to select new threshold range for next sequential images based on previous ones. Our proposed system is to active the range of hue for target recognition updated from previous recognized object.

The proposed lighting adaption algorithm is as follow:
1. Initiate recognition process using defined standard hue values for each basic color.
2. Select the sampling points in previous recognized object area through projection from estimated pose.
3. Get the hue value corresponding to each point on the image.
4. And automatically adjust the range of hue values to be used for follow-up recognition according to the distribution of the hue.

IV. Experimental Results and Discussion

A. Assumptions of Proposed Experiment

The information of the target object such as size, shape and color is foreknown to the system. In the 3D recognition process, it is assumed that the target object exists in the GA searching space. In the control system, the desired pose (x_d[mm], y_d[mm], z_d[mm] and ϵ_{2d}[deg]) between the target and the ROV are predefined so that the robot will perform regulating function through visual servoing. Controlling rotations around x and y-axes of $\sum_H$ as shown in Fig.6 (ϵ_{1d}[deg], ϵ_{3d}[deg]) are neglected because of their less effectiveness to ROV's motion in this experiment.

B. Visual Servoing under Dynamic Light Environment

The underwater experiment is conducted in a indoor pool. The size of the pool is 3[m] in length, 2[m] in width, 0.75[m]

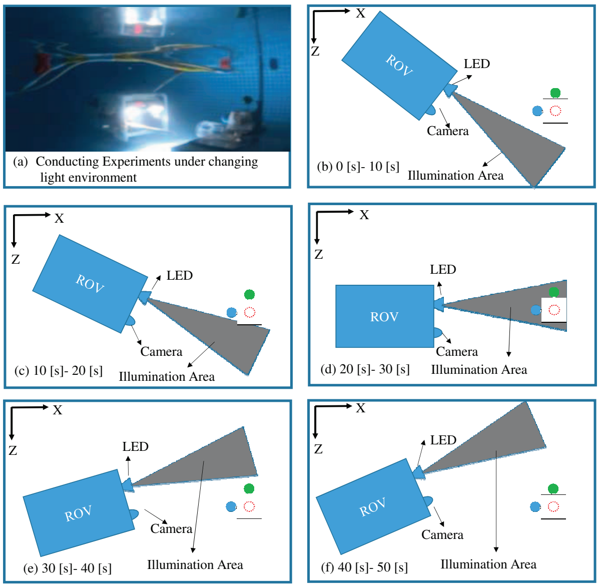

Fig. 10. Experimental Layout

in depth. Since LED light is dominant in deep sea, we simulated dynamic lighting environment for vehicle using its own light as shown in Fig.10. Combination of day light and LED light based on vehicle's moment especially in back and forth direction provides enough varying illumination intensity. However, according to limitation of pool space, the direction of LED lighting unit is configured to sweep up and down to offer dynamic lighting environment perfectly in term of both illumination intensity and direction as shown in Fig.10. LED light unit provides different illumination intensity and direction every 10 seconds.

We conducted visual servoing experiment with and without lighting adaptation system for the following conditions.

Condition 1: Visual Servoing under dynamic lighting environment when there is natural sun light to simulate the application in surface ocean where both day light and vehicle's light unit are dominant.

Condition 2: Visual Servoing under dynamic lighting environment when there is almost no natural sun light to simulate the application in night and deep ocean where only vehicle's light unit is dominant.

According to the range of camera for recognition and experimental environment scale, the desired pose is set as below. The negative distance in z-axis is the difference between origin of the camera and vehicle frame. In regulating performance, the vehicle keeps the constant relative pose to the target as defined below by mean of visual servoing.

$$x_d = {}^H x_M = 600[mm], \quad y_d = {}^H y_M = 0[mm],$$
$$z_d = {}^H z_M = -60[mm], \quad \epsilon_{2d} = 0[deg]$$

Fig.12 and Fig.13 show the performance of visual servoing under dynamic lighting environment when there is sunlight and when there is only vehicle's LED lighting respectively. In each of these figure, sub-figures (a)-(f) are the results of visual servoing without using proposed light adaptation system and sub-figures (m)-(r) are the results using proposed light adaptation. Please note that the fitness value is to measure the matching degree between recognized image and target. Therefore, a threshold level is defined in 3D model-based recognition to detect the target. In this case, according to the experimental result, we defined fitness value of 0.6 as a threshold level to detect the target object. In Fig.12(a) , when the light is directly to the object during 30s to 40s , the brightness makes fitness value reduce as the hue value of some object changes to white. In contract, the fitness value can be maintained using proposed system as shown in Fig.12(m). As shown in Fig.13(a), the effective of varying light condition can be seen significantly. Even though there are some fluctuation in fitness value using light adaptation system, it is neglectable time duration to interrupt the visual servoing performance as shown in Fig. 12(n)(o)(p). It can be seen in Fig.13(a) during period between 50s to 60s that the fitness value decrease below defined value 0.6 while conducting in no sun light condition. Consequently, the system started loosing control and the visual servoing performance decreases as shown in Fig.13(c). In contract, the recognition accuracy in term of fitness value and visual servoing performance can be maintained using proposed light adaptation system as shown in (m)-(p) in both condition 1 and 2.

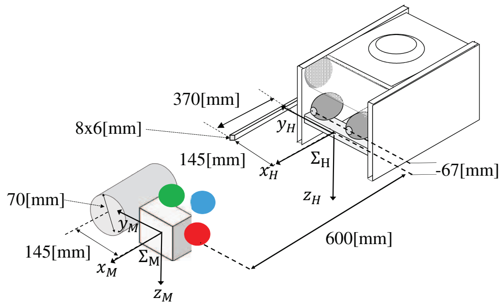

Fig. 11. Docking Experimental Layout

C. Docking Performance using Proposed System

Finally we conducted experiments to confirm whether the proposed system can operate docking task under unknown environment. In order to perform docking experiments, a rod on the right side of the underwater robot and cylinder hole on the left side of the target are designed as shown in Fig.11. When the robot is in the right relative pose to the object, then it has to move ahead to insert the rod into the cylinder hole. Fig.14(a) shows the fitness value of recognition during docking operation under unknown light environment.

$$x_d = {}^H z_M = 600\ (350)[mm],$$
$$y_d = {}^H x_M = 0\ (0)[mm],$$
$$z_d = {}^H y_M = -67\ (-67)[mm], \quad \epsilon_{2d} = 0\ (0)[deg]$$

Fitness value increases up to around 0.8 after applying adaptive system after 40 seconds. Fig.14(b)(c)(d) show the real-time position of vehicle during docking. The desired pose is defined as below. It should be noted that numbers in blacked () as below is defined target value at the time of fitting completion in docking experiment. When the desired pose is regulated within defined error threshold (that is less

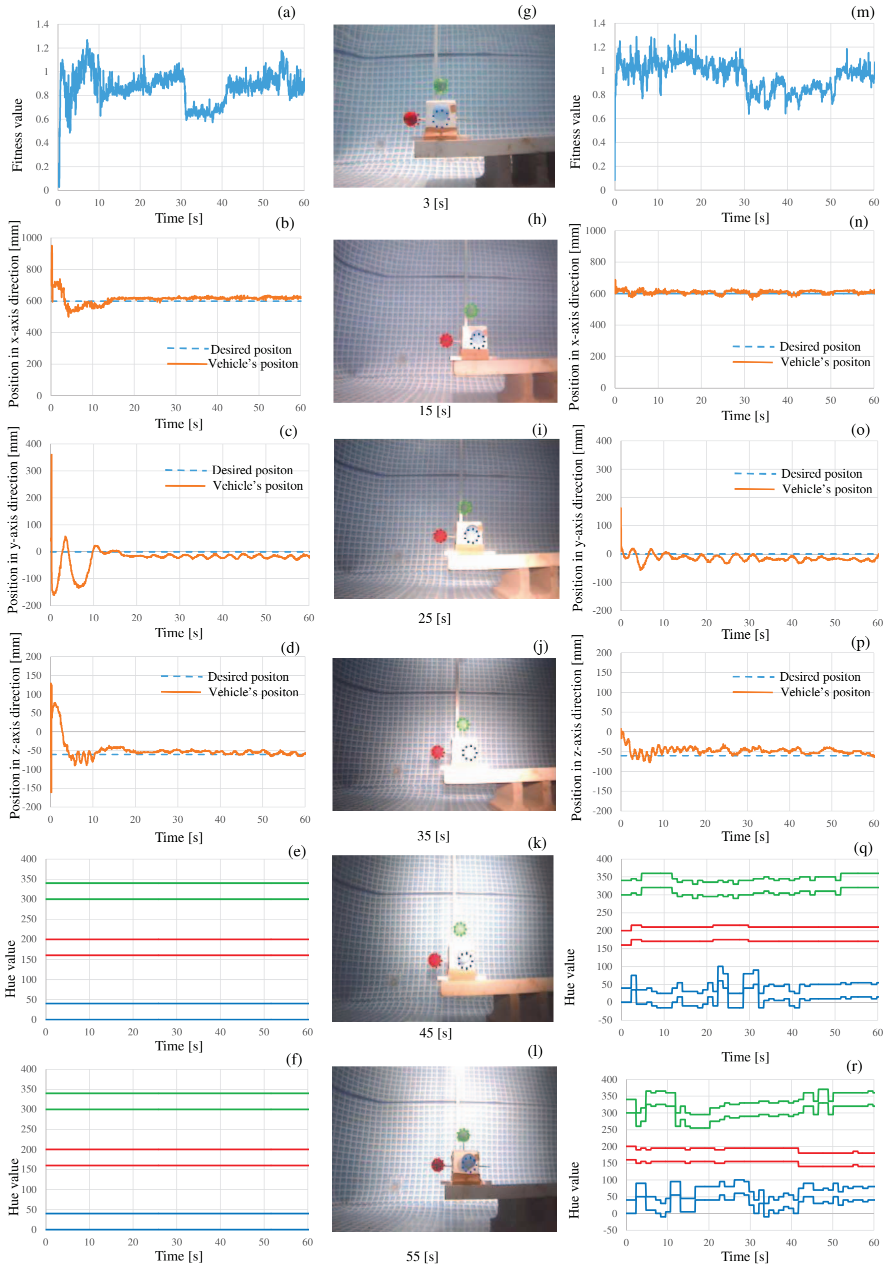

Fig. 12. Visual Servoing under dynamic light environment when there is natural lighting, (a)-(f) without using proposed light adaptation system and (m)-(r) using proposed light adaptation system, (e),(q) hue range to detect blue, red, green ball in left image, (f),(r) hue range to detect blue, red, green ball in right image

than 20 mm in this work) and stable for defined period (that is 165 ms in this experiment), then the vehicle moves ahead until(z_d=350[mm]). Finally, docking experiment under unknown lighting environment is completed successfully by only mean of virtual servoing using adaptive system following designed docking strategy with promising effectiveness as shown in Fig.14(b), where docking has been done during 50-80[s]. Fig.15 shows the photos of docking operation step by step.

V. Conclusion

In this paper, visual based docking system for underwater vehicle under dynamic light environment is proposed. A real-time pose detection scheme was implemented by means of 3D model-based recognition and 1-step GA using stereo vision and 3D marker as the passive target. Light Adaptation System for dynamic light environment is proposed and confirmed experimentally in simulated pool. Visual Servoing performance under varying light conditions shows the effectiveness of proposed system. Finally docking experiment was conducted successfully using proposed system under unknown light environment. Follow-up experiments in real sea trial will be

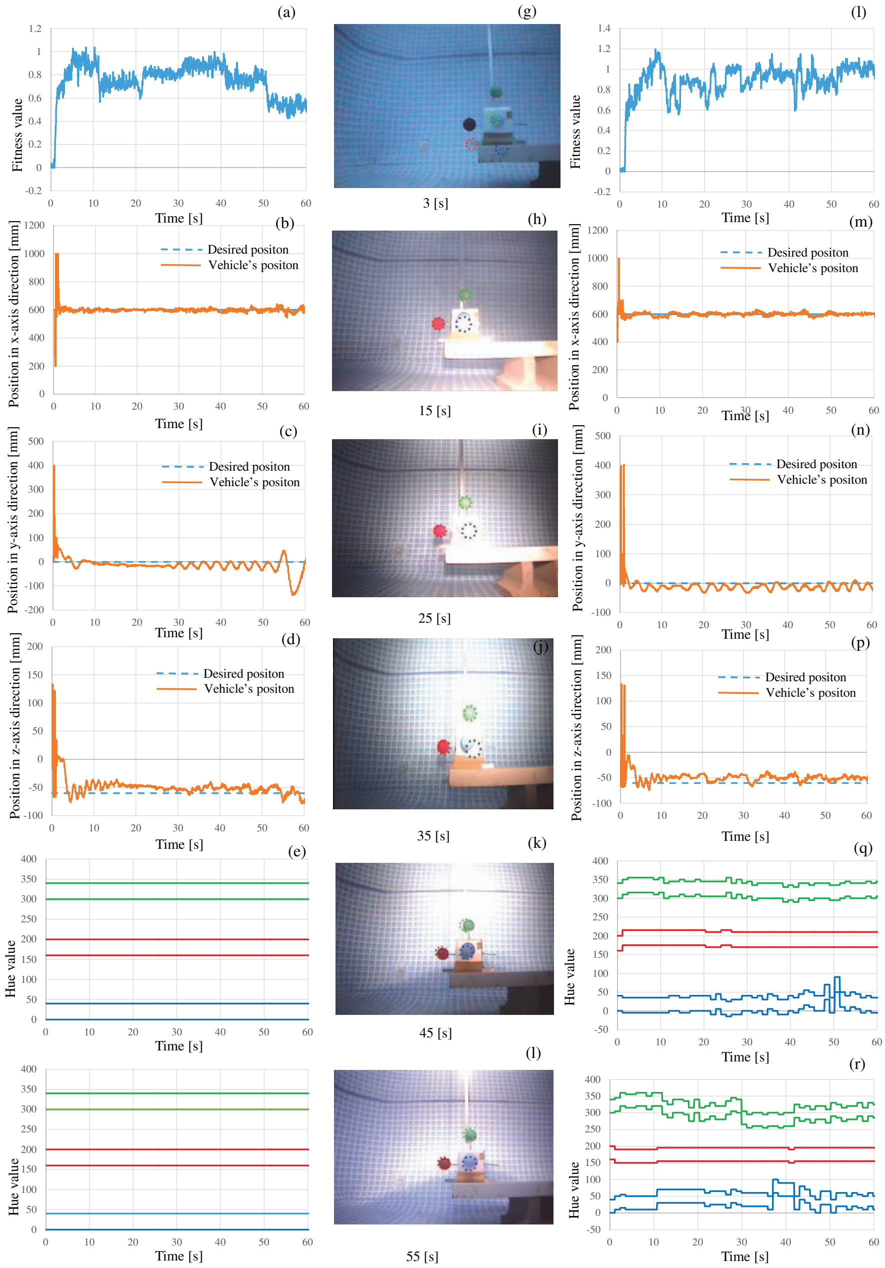

Fig. 13. Visual Servoing for dynamic light environment when there is no almost natural lighting,(a)-(f) without using proposed light adaptation system and (m)-(r) using proposed light adaptation system, (e),(q) hue range to detect blue, red, green ball in left image, (f),(r) hue range to detect blue, red, green ball in right image

conducted in near future.

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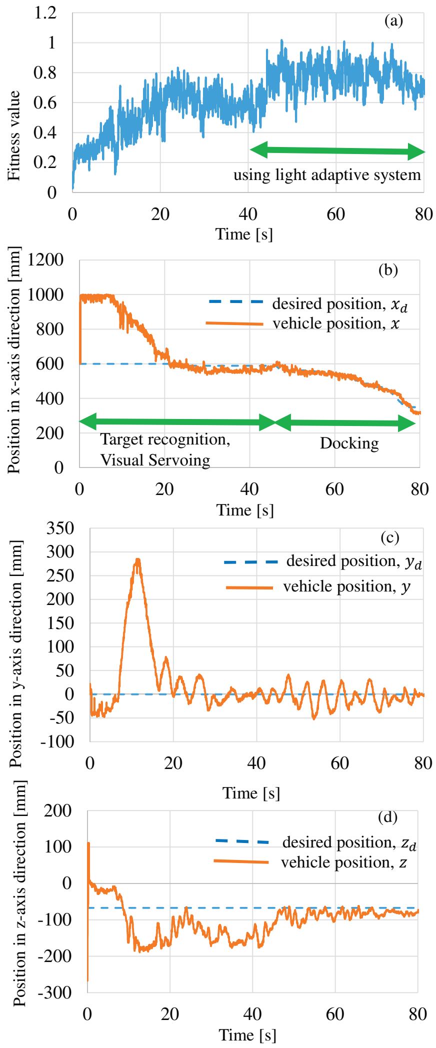

Fig. 14. Docking Performance with Lighting Adaptation System: (a) fitness value, (b) error in x-axis direction, (c) error in y-axis direction, (d) error in z-axis direction

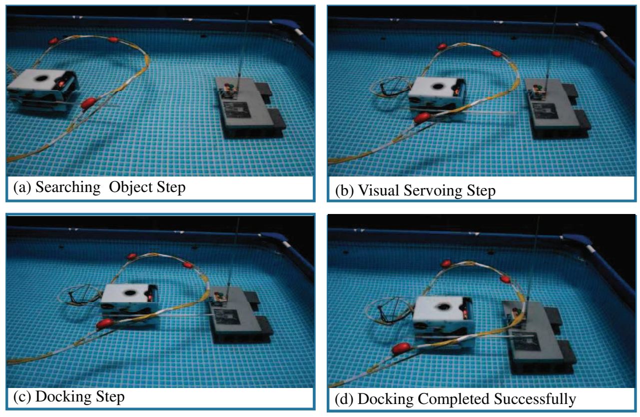

Fig. 15. Docking Process: (a) Searching Object Step, (b) Visual Servoing Step, (c) Docking Step, (d) Docking Completed Successfully

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