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

Underwater Box-pushing with Multiple Vision-based Autonomous Robotic Fish

Yonghui Hu[1, 2], Long Wang[1], Jianhong Liang[2], and Tianmiao Wang[2]
[1]*College of Engineering, Peking University, Beijing 100871, China*
[2]*School of Mechanical Engineering and Automation, Beihang University, Beijing 100191, China*
(E-mail: `huyhui@gmail.com`)

Abstract— **This paper presents an underwater cooperative box-pushing scenario in which three autonomous robotic fish that sense, plan and act on their own move an elongated box from some initial location to a goal location. With the onboard monocular camera, the robotic fish can estimate the pose of the object in the swimming tank. Considering the complexity of the underwater environment and the limited capability of a single robotic fish, we address the task by decomposing it into three subtasks and assigning them to capable robotic fish. With one robotic fish observing the box at the goal location and two robotic fish pushing the left and right ends of the box, the box can be moved gradually towards the goal location. The subtask consists a series of behaviors, each designed to fulfill one step of the subtask. The robotic fish coordinate through explicit communications and distribute the subtasks with a market-based dynamic task allocation method. Task reallocation mechanism that permits robotic fish to auction its assigned task to capable ones is used to cope with unexpected changes in the environment and the limited sensing range of the robotic fish. Experiments are conducted to verify the feasibility of the proposed methods.**

I. INTRODUCTION

Multirobot systems are being used increasingly in highly dynamic or adversarial environments to address complex tasks, such as planetary exploration [1], monitoring and surveillance [2], search and rescue [3], and transportation of large objects [4]. Like humans working in a team to achieve a common goal or a swarm of ants foraging for and hauling food together, a group of cooperating robots can perform certain tasks better than a single robot. By decomposing the task into subtasks and executing them concurrently, multi-robots can accomplish the task in a more efficient and robust manner. Moreover, many tasks not executable by a single robot can be tackled by a robot team by taking advantages of distributed sensing and actuation. However, the design and deployment of multirobot systems in real-world applications represent a formidable scientific challenge. Many problematic issues like group architecture, resource conflict, dynamic and unpredictable environments, noisy perception and limited communication bandwidth and range have to be dealt with in order to achieve effective teamwork.

Majority of multirobot systems are implemented in terrestrial or aerial environment, and few results have been obtained on underwater robots. Unprecise motion control due to the disturbance of waves and unknown currents, the lack of effective acoustic and optical sensors, unreliable underwater communication and high operational costs make it difficult to realize multirobot cooperation in hydro-environment. With the increasing human demand for exploitation and utilization of ocean resources, more research efforts should be devoted to the development of cooperating underwater robots. In recent years, biomimetic robotic fish, as a novel miniature underwater vehicle, has progressed considerably [5]. By emulating the swimming mechanisms of fish in nature, robotic fish can obtain enhanced locomotion performances over conventional screw-propelled underwater vehicles, such as high efficiency, great agility, increased noise reduction and station-keeping ability. Robotic fish can play an important role in various underwater tasks, especially those that require operations in cluttered environments and in unsteady flow. Most studies of robotic fish focus on the hydrodynamic modelling of swimming fish [6], [7] and building of artificial fish-like devices [8], [9], cooperative control of multiple robotic fish has seldom been investigated. The significance of the study of multiple robotic fish cooperation is twofold. From the engineering perspective, multiple cooperating robotic fish provide a feasible solution to a variety of complex underwater missions, which are intractable for a single robotic fish or difficult to be executed by other underwater robots. For example, in naval reconnaissance task multiple robotic fish can improve the performance of the task execution by sharing collected information while reduce the possibility of detection by pretending to be a real fish school. From the scientific perspective, the schooling behaviors of fish in nature can be recorded and better understood with the help of multiple robotic fish. The self-organizing mechanisms of fish can be emulated and verified with multiple robotic fish governed by a localized control regimen, and perhaps the grouping behaviors of fish might be deliberately harnessed to produce certain global patterns via multiple life-like robotic fish swimming together with live fish.

This paper is concerned with a cooperative underwater box-pushing task, which is one of the canonical task domains for terrestrial multirobot systems. Previously, cooperative transportation of a rectangular box with three robotic fish was implemented by Zhang *et al.* through a centralized approach [10]. In that scenario, the pose information (position and orientation) of the robotic fish and the box within a swimming tank are captured by an overhead camera. A host computer, which does online analysis and planning, sends

978-1-4244-6676-4/10/$25.00 ©2010 IEEE

commands to the robotic fish to generate coordinated box-pushing actions. As has been extensively discussed in the literature, although the centralized approach can produce optimal coordination, it responses sluggishly to environment changes and is vulnerable to the failure of the central planning unit. Besides, the centralized approach for multi-fish cooperation is unfeasible in open water environment where the overhead camera for information gathering is not available. Contrarily, decentralized approach in which the robotic fish plan actions based on their local observations can circumvent the above problems. Recently, we have developed a vision-based autonomous robotic fish which can sense, plan and act on its own [11]. On the basis of this work, we further investigate decentralized approach to the box-pushing task with multiple autonomous robotic fish. Without any global information about the posture of the box and themselves, the robotic fish should cooperate by sharing visual information and execution ability in order to move the box from its initial location to the designated goal location.

The remainder of this paper is structured as follows. Section II gives the specifications of the box-pushing task and the coordination methods. Experimental results are presented in Section III. Finally, concluding remarks are drawn in Section IV.

II. COORDINATED BOX-PUSHING WITH MULTIPLE ROBOTIC FISH

A. Task Description

Fig.1 shows the settings of the underwater box-pushing task. Three robotic fish which are randomly positioned in the swimming tank at the beginning are required to move a rectangular box from some initial location to an observable goal location. With the mechanical structure described above, the robotic fish can move the box by pushing against it. Because the box is large relative to the size of the robotic fish and the fluid drag is considerable, single robotic fish is incompetent to move the box alone. In addition, when the robotic fish pushes the box with its front end where the camera locates it cannot perceive the goal simultaneously due to occlusion, so that it has to share sensory information with other robotic fish in order to conduct effective pushing. Therefore coordinated pushing with multiple robotic fish is a viable solution to this problem.

Compared with box-pushing in terrestrial environment, the underwater box-pushing task is more difficult. The complexity of the aquatic environment and peculiarities of the propulsion mode of robotic fish pose several issues to the successful fulfillment of the underwater task, which are listed below:

- Unlike ground wheeled vehicles instrumented with optical encoders for speed feedback of wheel rotation, the translational and rotational velocities of the robotic fish can not be precisely sensed and controlled.
- The underwater image is plagued by several factors including distance-dependent visibility, ambient light, scattering and absorption, which make it difficult to perceive the box and the target accurately.

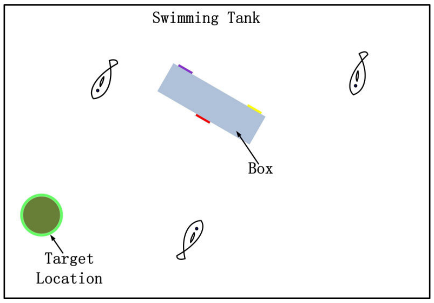


Fig. 1. Illustration of underwater box-pushing task.

- Desired position and orientation of the box can hardly be reached with pushing actions due to the apparent effect of inertial drift in underwater environment.
- Waves occur when the robotic fish flaps to swim. The motion of the robotic fish and the box will be mutually affected through the coupling of waves, which further complicates the problem.

B. Vision Processing and Object Pose Estimation

Each object within the swimming task is marked with specified colors. The goal of vision processing is to identify the colored object of interest using the monocular camera and to estimate the distance and bearing of each object with respect to the robotic fish. Given the dynamic nature of the task and the full autonomy of the robotic fish, the vision algorithms should be both robust and efficient, consuming only a fraction of the CPU resources and leaving the remainder of computing capability for robot cognition. The vision algorithm consists of the following steps which are performed in a consecutive order on each frame:

- Thresholding: This step is to map each pixel in the raw YCbCr image into a color class label based on a threshold rectangular in the Cb and Cr chrominance dimensions.
- Blob formation: In this step, neighboring pixels belonging to the same color class are grouped together and merged into a single structure called blob.
- Extracting blob information: For each blob, the following statistics are calculated: centroid, bounding box and area. Blobs of the same color are then sorted by area so that the largest blobs with area bigger than a threshold value can be identified as valid object.

The color fiducials of the objects are designed to be of specific shape and with unique color. The goal location is specified with a post wrapped with a green strip. The box is attached with a red square fiducial in the middle of one side and purple and yellow fiducials on two ends of the other side. The robot coordinate system $X_R Y_R Z_R$ has its origin at the focal point of the camera, its X_R-axis pointing forward, its Y_R-axis pointing through the left-hand side and its Z_R-axis pointing upward. The robotic fish swims in the horizontal plane and the vertical distance from the camera to the center of fiducials remains constant. Given the size of the fiducials and the information of corresponding projected color blobs,

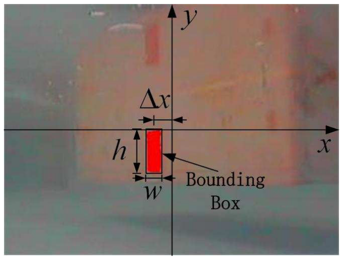


Fig. 2. The projected color blob of the red square fiducial on the box.

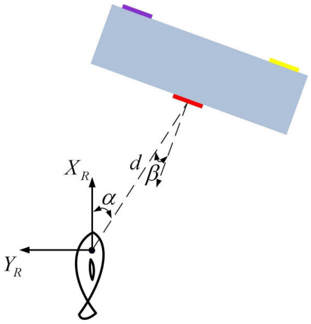


Fig. 3. Illustration of parameters in object pose estimation.

the pose of the objects measured in the robot coordinate system can be estimated on the basis of a pinhole camera model [12].

The projected image of a square fiducial will appear in the image plane with a projection distortion as shown in Fig. 2. The height of the bounding box is h, the width is w and the offset from the center of the bounding box to the center of image in the x direction is Δx. The side length of the square fiducial is L. The posture estimates of the object, as illustrated in Fig. 3, can be calculated as:

$$d = f\frac{L}{h} \tag{1}$$

$$\alpha = \Delta x \frac{\gamma}{X_{res}} \tag{2}$$

$$\beta = \begin{cases} arccos(\frac{w}{h}) & \text{if the color blob is higher} \\ & \text{on the left side} \\ -arccos(\frac{w}{h}) & \text{otherwise} \end{cases} \tag{3}$$

where d is the distance between the robotic fish and the object, f denotes the focal length of the camera, α represents the angle between the heading direction and the direction to object, γ and X_{res} are camera parameters representing the horizontal filed of view and the horizontal resolution of the camera respectively, and β is the angle of incidence to the object.

C. Decomposition of Underwater Box-Pushing Task

The division of labor mechanism has been widely used by human and animals to address complex tasks. By breaking the task up into smaller pieces and assigning jobs to capable team members, the performance of the task can be maximized. Considering the requirements and settings of the underwater box-pushing task, we propose here a multirobot cooperative underwater transportation system in which two robotic fish are responsible for pushing the box whereas the third robotic fish acts as a environment-embedded sensor for pose perception of the box. With this division of labor approach, the overall box-pushing task can be decomposed by hand into the following three subtasks: Push-Left, Push-Right and Observe. Each subtask can be executed completely by a single robotic fish. The robotic fish that carry out the Push-Left and Push-Right subtasks can see the yellow and purple fudicials on the box respectively, while the robotic fish performing the Observe subtask is positioned at the goal location and can see the red fiducial on the opposite side of the box. The observing robotic fish calculates the pose of box and communicates with the pushing robotic fish to ensure that the box is moved towards the goal location. The scenario of coordinated underwater box-pushing with three robotic fish is illustrated in Fig.4.

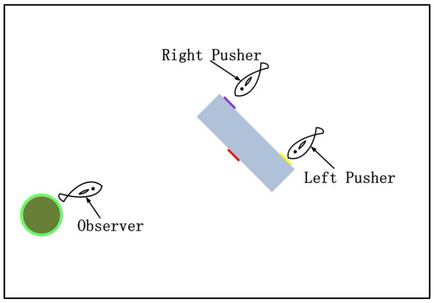


Fig. 4. Scenario of coordinated box-pushing with three robotic fish.

The subtask can be achieved with a set of related behaviors, each designed to execute one stage of the subtask. The behaviors are executed in sequence and the transition from one behavior to another is triggered by real-time perception of the robotic fish. To reduce the oscillations at the anterior part of the robotic fish caused by the flapping movements of the tail fin, a hybrid swimming pattern is utilized for each behavior. This swimming pattern, which has been experimentally validated to produce minimum oscillations at the head, uses synchronized pectoral fins for thrust generation and tail fin as a rudder.

The Push-Left and Push-Right subtasks are designed in the same way and we will take the Push-Left subtask as an example to illustrate their implementation details. The robotic fish assigned with the Push-Left subtask has the corresponding end of the box in its field of view (FOV). To perform the task, the robotic fish must swim towards the left end of the box until it has contact with the box and then start pushing the box with its head. The Push-Left subtask includes the following two primitive behaviors:

- Approach-Box-Left-End: This behavior consists in attracting the robotic fish to the left end of the box. The flapping frequency of the pectoral fins, which determines the translational speed of the robotic fish, varies with distance to the target. Outside a controlled zone, the robotic fish swims at maximum speed. When the robotic fish enters the controlled zone, the flapping

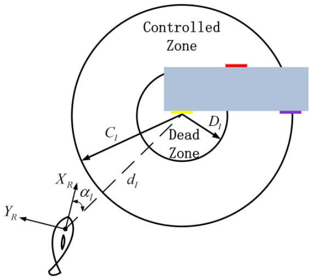


Fig. 5. Illustration of parameters in Approach-Box-Left-End behavior.

frequency decreases linearly from maximum to zero. Within the dead zone, the robotic fish stops flapping pectoral fins and slowly drifts to the box in order to realize soft contact with the box. This behavior terminates 0.5s after the robotic fish enters the dead zone. Although it is rather difficult to achieve zero speed when the robotic fish docks at the box, any fierce collision can be avoided with the above speed control method. The swimming direction of the robotic fish is controlled with the angular offset of tail fin. A simple proportional controller is used to regulate the swimming direction of the robotic fish. The motion of the robotic fish is governed by the following equations:

$$f_p = \begin{cases} f_p^{max} & \text{if } d_l > C_l \\ \frac{(d_l - D_l) f_p^{max}}{C_l - D_l} & \text{if } D_l < d_l \leq C_l \\ 0 & \text{if } d_l \leq D_l \end{cases} \tag{4}$$

$$\phi_t = K_l \alpha_l \tag{5}$$

where f_p^{max} is the maximum flapping frequency of the pectoral fins, d_l is the distance from the robotic fish to the fiducial on the left end of the box, K_l is the gain of the proportional controller, α_l is the angle between the heading direction of the robotic fish and the direction to the left end of the box, C_l and D_l specify the radii of the controlled and dead zone respectively. Fig. 5 illustrates the parameters used in this behavior.

- Push-Box-Left-End: The robotic fish executes this behavior to exert a pushing force on the left end of the box so that the pose of the box can be changed. To push the box in an effective manner, the robotic fish flaps its pectoral fins with maximum frequency. As the box moves, the robotic fish regulates the angular offset of the tail fin with a proportional controller to keep touch with the left end of the box with its head. The robotic fish is controlled by:

$$f_p = f_p^{max} \tag{6}$$

$$\phi_t = K_l \alpha_l \tag{7}$$

The function of the Observe subtask is to direct the pushing robotic fish based on visual perception at the goal location. The observing robotic fish first swims to the proximity of the goal, swirls to search the box and then starts guiding the pushing robotic fish. The following primitive behaviors are linearly combined to realize the Observe subtask:

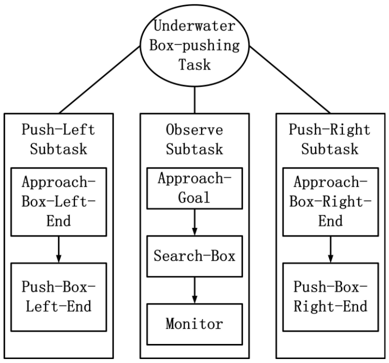


Fig. 6. Decomposition scheme of the underwater box-pushing task.

- Approach-Goal: This behavior enables the robotic fish to swim towards the goal location. The robotic fish swims with maximum speed until it gets reasonably close to the goal and switches to the next behavior. A proportional controller is used to control the angular offset of the tail fin. The equations that determines the motion of the robotic fish are:

$$f_p = f_p^{max}\ , \quad \text{for } d_g > C_g \tag{8}$$

$$\phi_t = K_l \alpha_l \tag{9}$$

  where d_g is the distance from the robotic fish to the goal and C_g is a threshold distance for this behavior.
- Search-Box: With this behavior, the robotic fish swirls to find the box. While flapping its pectoral fins with maximum frequency, the tail fin is biased $\frac{\pi}{3}$ to the left or right side. The effected motion with this behavior is turning clockwise or counterclockwise with a small radius. The mathematical formulation of this behavior is:

$$f_p = f_p^{max} \tag{10}$$

$$\phi_t = \frac{\pi}{3} \text{ or } -\frac{\pi}{3} \tag{11}$$

- Monitor: The robotic fish executes this behavior when it has found the box. Although the robotic fish doesn't move with this behavior, a series of complex operations are performed. The robotic fish continuously estimates the pose of the box, and then directs the other robotic fish to push the box towards itself with a coordination protocol. The implementation details of the coordination methods are described in the following subsection.

With the above task decomposition scheme, the underwater box-pushing scenario can be executed concurrently with the three robotic fish. Fig. 6 shows the decomposition scheme of the underwater box-pushing task.

The robotic fish that is not performing any of the subtasks executes Safe-Wander behavior, which enables random motion without colliding with obstacles, i.e., the box or other robotic fish. Both the flapping frequency of the pectoral fins and angular offset of the tail fin are randomly generated if there is no obstacle in the FOV or the obstacle is far away, otherwise the robotic fish turns to avoid the obstacle. The control parameters of this behavior are determined as:

$$f_p = f_p^{rdm} \tag{12}$$

$$\phi_t = \begin{cases} \phi_t^{rdm} & \text{if no obstacle in FOV or } d_o > C_o \\ \frac{\pi}{3} & \text{if } d_o \leq C_o \text{ and } \alpha_o < 0 \\ -\frac{\pi}{3} & \text{if } d_o \leq C_o \text{ and } \alpha_o \geq 0 \end{cases} \tag{13}$$

where f_p^{rdm} and ϕ_t^{rdm} are random values that are periodically generated, d_o denotes the distance from the robotic fish to the obstacle, C_o is a threshold distance, and α_o is the angle between the heading direction of the robotic fish and the robot-to-obstacle direction.

D. Dynamic Task Allocation

The successful fulfillment of the underwater box-pushing task requires to determine which robotic fish should execute which subtask, also known as the task allocation problem in multirobot systems. Given the dynamic nature of the underwater environment and the motion uncertainties of the box, the assignment of robotic fish to subtask is a dynamic process and needs to be continuously adjusted to improve overall system performance. Dynamic task allocation among the robotic fish is achieved through deliberate communications and negotiations. After introducing the communication infrastructure of the team of robotic fish, the market-based dynamic task allocation method for the underwater box-pushing task will be presented.

The robotic fish negotiate with each other through explicit communications using the onboard serial RF communication hardware. Messages are broadcast at baud rate of 19200 bits per second to all of the robotic fish. Each robotic fish has a unique id number that identifies it in the communication network. To guarantee collision-free access to the radio channel, a timed token-passing protocol is employed. There exists a token travelling between the robotic fish in a circular fashion and each robotic fish can transmit messages only when it possesses the token. The basic idea is to assign each robotic fish a time budget, which is the maximum time the robotic fish is permitted to speak every time it receives the token. In case the robotic fish holding the token malfunctions and fails to forward the token, a timer on the next robotic fish expires and a new token can be created to recover from the system failure.

Market-based approaches have gained considerable popularity as flexible and efficient mechanisms for distributed task allocation in multirobot systems [13], [14]. Inspired by the original Contract Net Protocol of Smith [15], market-based approaches use auction mechanisms for task allocation. In these approaches, tasks available to be allocated are put up for auction and candidate robots submit bids that are their cost or utility estimates associated with completing the tasks. Once all bids have been received or a prespecified deadline has passed, the auctioneer evaluates all the submitted bids and awards the robot with the highest bid a contract to execute the tasks. In the underwater box-pushing scenario, tasks are allocated via a sequence of single-item sealed-bid auctions, in which tasks are auctioned one at a time and the bidder submits its bid honestly without knowing the other's bid.

At the start, all robotic fish execute Safe-Wander behavior and a host computer, acting on behalf of the human supervisor, announces the Observe subtask. The robotic fish receive the information about the task being auctioned and then respond with a bid. The value of the bid is estimated by the robotic fish based on its perceived path cost to the goal location, which is calculated as:

$$U = \begin{cases} \frac{k_1}{d_g} + \frac{k_2}{|\alpha_g|} & \text{if the goal is in FOV} \\ 0 & \text{otherwise} \end{cases} \tag{14}$$

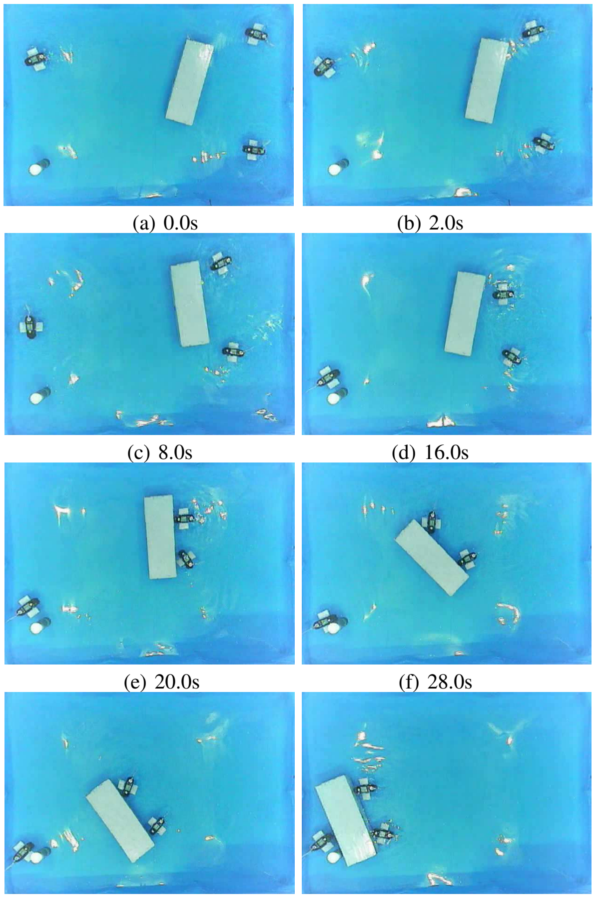
where α_g represents the angle between the heading direction of the robotic fish and the robot-to-goal direction, k_1 and k_2 are positive constant parameters. Once the host computer receives all bids, it informs the robotic fish with the highest bid to perform the Observe subtask. If the goal is not observable to all robotic fish, i.e., all robotic fish submit zero-valued bids, the auctioneer will continuously broadcast the Observe subtask until it is allocated.

Once the robotic fish is assigned with the Observe subtask, it will consecutively execute Approach-Goal behavior, Search-Box behavior, and finally Monitor behavior. With Monitor behavior, the robotic fish periodically auctions Push-Left and Push-Right subtasks according to the pose of the box. The other two robotic fish bid the pushing subtasks with their position estimates with respect to the left and right ends of the box. The angle of incidence β_b to the box is used to decide which subtask should be auctioned. If β_b is greater than a threshold value β_b^{thr}, only the Push-Left subtask is auctioned; when $\beta_b < -\beta_b^{thr}$, only Push-Right subtask is announced; otherwise both subtasks are auctioned. The contract of a pushing task is considered overdue by the observing robotic fish when the orientation of the box is changed so significantly that new pushing strategy should be employed. The robotic fish cannot hold two or more tasks at the same time, therefore only robotic fish with no assigned task can bid newly-announced tasks.

Since the task environment is dynamic and complex, the robotic fish may fail to achieve the task it has committed to. For example, when the robotic fish assigned with Observe subtask executes Approach-Goal behavior, other robotic fish may appear in its FOV and occlude the goal. A pushing robotic fish may also lose sight of the box due to the unpredictable motion of the box caused by waves or the pushing of other robotic fish. To cope with these situations, we allow for re-auctioning task when the robotic fish is no longer competent for its assigned task. In the auction algorithm of task reallocation, the auctioneer itself can also bid the task in case it will become suitable for the task again. The task re-allocation mechanism is especially useful in the underwater box-pushing task, since the environment is highly dynamic and the sensing capability of robotic fish is very limited.

III. EXPERIMENTS

The underwater box-pushing experiments with three robotic fish are conducted in an indoor swimming tank. A host computer, which connects with a RF communication module, is used to assign the Observe subtask to the robotic fish at the beginning. The box is initially positioned in such a posture that the robotic fish at the goal location can see the side attached with red fiducial.



(a) 0.0s (b) 2.0s

(c) 8.0s (d) 16.0s

(e) 20.0s (f) 28.0s

(g) 36.0s (h) 44.0s

Fig. 7. Experiment scenarios of underwater box-pushing.

Typical experiment scenarios of the underwater box-pushing task are shown in Fig. 7. The goal is located at the bottom-left corner of the swimming tank. Fig. 7(a) shows the initial scenario in which three robotic fish that are randomly positioned in the swimming tank start by executing Safe-Wander behavior and the host computer auctions the Observe subtask. At 2.0s in Fig. 7(b), the robotic fish on the left sees the goal and gets the Observe subtask. As shown in Fig. 7(c), the robotic fish assigned with Observe subtask swims towards the goal location while the other two robotic fish still execute Safe-Wander behavior. After the robotic fish on the left arrives at the goal location, it turns around to face the box and then starts auctioning Push-Left and Push-Right subtasks (see Fig. 7(d)). The other two robotic fish bid the pushing subtasks and move the box by pushing against the fiducials that correspond to their allocated tasks. In Fig. 7(e)-(g), the box floats gradually towards the observing robotic fish. The orientation of the box is adjusted by repeated pushing on its left and right ends. At 44.0s, the box is successfully moved to the goal location, as shown in Fig. 7(h).

IV. CONCLUSIONS

This paper has addressed the underwater cooperative box-pushing problem involving three autonomous robotic fish, each equipped with a monocular camera. Our solution is based on a division-of-labor approach that decomposes the task into an observing subtask and two pushing subtasks. Behaviors used to execute one step of the subtask are designed and linearly combined to fulfill the subtask. The robotic fish coordinates through explicit communications and the allocation of subtask to robotic fish is addressed with a market-based task allocation method. To cope with the complexity of the underwater environment and the limited perception of the robotic fish, a task reallocation mechanism that allow robotic fish to auction its task to competent ones is used. Experimental results verify the feasibility of the proposed methods.

REFERENCES

[1] M. J. Mataric, and G. S. Sukhatme, “Task allocation and coordination of multiple robots for planetary exploration,” in *Proc. Int. Conf. Advanced Robotics*, Buda, Hungary, August 2001, pp. 61-70.

[2] A. Kolling, and S. Carpin,“Multirobot surveillance: an improved algorithm for the GRAPH-CLEAR problem,” in *Proc. IEEE Int. Conf. Robotics and Automation*, Pasadena, California, May 2008, pp. 2360-2365.

[3] M. Koes, I. Nourbakhsh, and K. Sycara, “Constraint optimization coordination architecture for search and rescue robotics,” in *Proc. IEEE Int. Conf. Robotics and Automation*, Orlando, Florida, May 2006, pp. 3977-3982.

[4] G. A. S. Pereira, M. F. M. Campos, and V. Kumar, “Decentralized algorithms for multi-robot manipulation via caging, ” *Int. J. Robotics Res.*, vol. 23, no. 7-8, pp. 783-795, 2004.

[5] P. R. Bandyopadhyay, “Trends in biorobotic autonomous undersea vehicles,” *IEEE J. Oceanic Eng.*, vol. 30, no. 1, pp. 109-139, 2005.

[6] F. E. Fish, and G. V. Lauder, “Passive and active flow control by swimming fishes and mammals,” *Annual Review of Fluid Mechanics*, vol. 38, pp. 193-224, 2006.

[7] G. V. Lauder, and E. D. Tytell, “Hydrodynamics of undulatory propulsion,” *Fish Biomechanics*, vol. 23 in Fish Physiology, pp. 425-468, 2006.

[8] M. S. Triantafyllou, and G. S. Triantafyllou, “An efficient swimming machine,” *Sci. Amer.*, vol. 272, no. 3, pp. 64-70, 1995.

[9] Y. Hu, L. Wang, W. Zhao, Q. Wang, and L. Zhang, “Modular design and motion control of reconfigurable robotic fish,” in *Proc. Int. Conf. Decision and Control*, New Orleans, Louisiana, December 2007, pp. 5156-5161.

[10] D. Zhang, L. Wang, J. Yu, and M. Tan, “Coordinated transport by multiple biomimetic robotic fish in underwater environment,” *IEEE Trans. Control System Technology*, vol. 15, no. 4, pp. 658-671, 2007.

[11] W. Zhao, Y. Hu, G. Xie, L. Wang, and Y. Jia, “Development of vision-based autonomous robotic fish and its application in water-polo-attacking task,” in *Proc. American Control Conf.*, Seattle, Washington, June 2008, pp. 568-573.

[12] M. Sonka, V. Hlavac, and R. Boyle, *Image Processing, Analysis, and Machine Vision, 2nd Edition*, PWS Publishing, Pacific Grove, 1999.

[13] M. B. Dias, R. Zlot, N. Kalra, and A. Stentz,“Market-based multirobot coordination: a survey and analysis,” *Proc. of the IEEE*, vol. 94, no. 7, pp. 1257-1270, 2006.

[14] B. P. Gerkey, and M. J. Mataric, “Sold!: auction methods for multi-robot coordination,” *IEEE Trans. Robotics and Automation*, vol. 18, no. 5, pp. 758-768, 2002.

[15] R. G. Smith, “The contract net protocol: high-level communication and control in a distributed problem solver,” *IEEE Trans. Comput.*, vol. C-29, no. 12, pp. 1104-1113, 1980.