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Design and attitude control of a novel robotic jellyfish capable of 3D motion

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Aquatic creatures such as fish, cetaceans, and jellyfish could inspire innovative designs to improve the ways that manmade systems operate in and interact with aquatic environments [1, 2]. Jellyfish in nature use jet propulsion to move through the water, which have been proven to be one of the most energetically efficient swimmers on the planet [3]. Researchers are making an integrated effort to develop smart actuators to fabricate various robotic jellyfish, such as shape memory alloys (SMA) [4], ionic polymer metal composites (IPMC) [5], and dielectric elastomer actuator [6]. Most of existing robotic jellyfish cannot freely adjust their three-axis attitude, which has an adverse effect on free-swimming propulsion and plausible applications. We investigate how to design and control a bio-inspired motor-driven robotic jellyfish capable of three-dimensional (3D) motion. The main contributions of this work are twofold. First, a novel 3D barycenter adjustment mechanism is implemented, allowing flexible regulation of the robot's barycenter. Second, the proposal of the reinforcement learning based attitude control method makes autonomous attitude regulation possible. In comparison with most of the other robotic jellyfish, the built robot displays a high order of structure flexibility and yaw maneuverability. Therefore, this self-propelled robotic jellyfish with 3D motion has great implications for bio-inspired design of jet propulsion system with great agility.

Development of the robotic prototype. As illustrated in Figure 1, the developed robotic jellyfish, which models after *Aurelia aurita* (commonly termed moon jellyfish), is hemispherical in shape and consists of a bell-shaped rigid head, a cylindroid main cavity, four separate six-bar linkage mechanisms, and a soft rubber skin. Considering most existing robotic jellyfish lacking turning capability, a barycenter adjustment mechanism for flexible attitude control is introduced. Specially, the barycenter adjustment mechanism is created through both horizontally and vertically altering the relative position of two clump weights. Each clump weight is connected to a step motor by a rocking bar and a gear set. Regulating the center of the gravity (CG) of the barycenter adjustment mechanism will cause change of CG of the overall robotic system over time, allowing 3D spherical change of the barycenter.

Reinforcement learning based attitude control. Reinforcement learning relies on trial-and-error mechanism, which has been investigated and utilized in many fields such as artificial intelligence and machine learning. As a type of model-free reinforcement learning, Q-learning can be used to solve the optimal value problems and the optimal policy problems in Markov decision processes (MDP) [7–9]. The goal of Q-learning is to find a policy π^* that maximizes the reward received by the agent over time. For a policy $\pi : s_t \to a_t$, define the Q value (action-value) as

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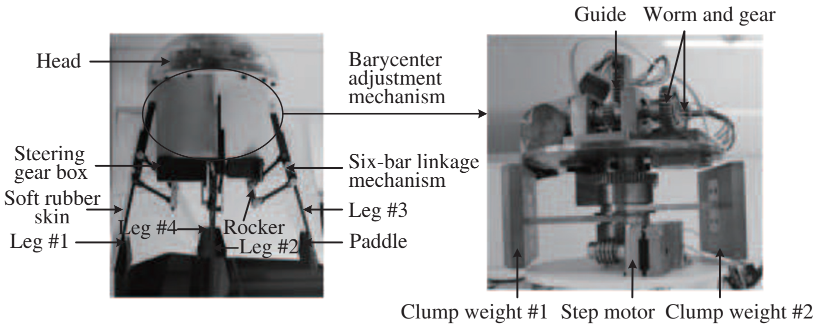

Figure 1 Mechanical design of the developed robotic jellyfish.

$$Q^{\pi}(s_t, a_t) = r(s_t, a_t) + \gamma \sum_{s_{t+1}} p_{s_t s_{t+1}} (\pi(s_t)) V^{\pi}(s_{t+1}), \quad (1)$$

where the first term $r(s_t, a_t)$ denotes the immediate reward received by the agent executing action at state s_t. The second term indicates the expected sum of future discounted rewards, where γ is the discount factor ($0 < \gamma < 1$) trading off the importance of sooner versus later rewards, and $p_{s_t s_{t+1}}$ is the probability of the state transfers from s_t to s_{t+1}. $V^{\pi}(s_{t+1})$ is the value of the expected return obtained from the state s_t according to the policy behavior π. Then, the optimal policy $\pi^* : S \to A$ can be defined as follows:

$$\pi^* = \arg\max_{a_t} Q(s_t, a_t). \quad (2)$$

In fact, state transition probabilities and rewards cannot be explicitly acquired in many realistic problems such as robotic control, but must estimate them from data. At each state s_t, the agent performs an action at using the obtained policy with the highest estimated action-value, and observes a reward $r(s_t, a_t)$ and a new state s_{t+1}. The Q value is then updated as follows:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha \Big[r(s_t, a_t) + \gamma \max_{a_{t+1}} Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t) \Big], \quad (3)$$

where α ($0 < \alpha \leqslant 1$) denotes the learning rate. Note that in one-step Q-learning, the policy used to choose an action is not related to the update policy, which is termed as the off-policy learning.

Generally, the attitude control involves three different angles of yaw, pitch, and roll. Considering that the mechanical structure of the robotic jellyfish is centrosymmetric, we can achieve 3D motion without controlling the roll angle. As for the yaw and pitch angles, we divide them into some equal parts, termed state boxes, instead of controlling the angle directly. The state boxes correspond to the states in reinforcement learning. Regulation of the clump weights leads to change of the barycenter of the robotic jellyfish and mainly determines the robot's attitude. In practice, step motor rotation control is the source of regulation of the clump weights. Hence, rotational outputs of step motor correspond to the actions in reinforcement learning. In the meanwhile, the relationship between the step motor rotation action and state boxes constitutes the action/state space.

Regarding the Q-learning, the reward definition and function are very important. In our control strategy, we set two variables: a target state box (target angle) and a current state box (actual angle). When an action increases the absolute value of difference of target angle and actual angle (i.e., the actual angle gets more far from the target angle), we regard it as a bad action and define the reward as a negative one. Correspondingly, when an action leads to the decrease of the absolute value of difference of target angle and actual angle (i.e., the actual angle gets closer to the target angle), we regard it as a good action and define the reward as a positive one. Thus, we can use the Q-learning function to make robotic jellyfish reach any desired target attitude.

Results and discussion. To validate the proposed mechatronic design and propulsive performance of the developed robotic jellyfish, extensive aquatic experiments were conducted in an indoor pool with dimensions 5 m long, 4 m wide, and 1.4 m deep.

The first experiment focused on the vertical balance attitude learning. In this experiment, we set the target angle as a pitch of 90°. The robotic jellyfish was required to achieve vertical balance state from a zero pitch angle. According to the experimental results, it took about 20 s to achieve the attitude regulation, i.e., the pitch angle was close to 90°. During this regulation, the clump weight horizontally traversed an angle of 120°, corresponding to a speed of 90°/s, whereas a vertical speed of 1.1 mm/s was accompanied.

The second experiment focused on a hybrid motion interweaving vertical and horizontal swimming via the learning attitude control strategies. In this experiment, we set a series of dynamic angles including compound changes of the target yaw and pitch. Specifically, the robotic jellyfish firstly swam down by using vertical jet propulsion mode, and then it shifted to horizontal forward swimming by regulating the barycenter adjustment mechanism, followed by horizontal turning motion. Based on the experimental results, during the horizontal turning motion, the pitch angle altered from a negative angle around -50° to about 0°, whereas the yaw angle almost maintained constant. When the robotic jellyfish performed horizontal turning motion by varying phase differences among legs, the yaw angle changed steadily. Further, through analyzing the time histories of attitude angles, it was found that a yaw turning speed of 5.6°/s and a pitch speed of 3.6°/s were obtained, revealing enhanced 3D motion capability.

As an intuitive type of movement, jellyfish-like jet propulsion offers inspiration to design novel underwater robots. Depending on the multi-linkage propulsive mechanism and barycenter adjustment mechanism, the developed robotic jellyfish successfully replicates jellyfish-like 3D motion capability in aquatic environments. In particular, both vertical and horizontal motions are integrated on the same self-propelled robotic platform. Thanks to the reinforcement learning, the robotic jellyfish learns to regulate its attitude automatically, eliminating the need of manual regulation of the robotic barycenter. According to the authors' knowledge, this may be the first time that the self-propelled robotic jellyfish has the ability to swim vertically and horizontally in 3D space.

Despite successfully implementing relatively flexible 3D motion, the robotic jellyfish has some limitations. First, the proposed barycenter adjustment mechanism involves three stepper motors along with the gear transmission systems, corresponding to a large volume of space and a high energy consumption. A compact and lightweight package will save additional space for load and power supply, leading to better practicality. Second, it is very time-consuming to train parameters of the reinforcement learning, and complexity and uncertainty in aquatic experiments bring an increased level of difficulty. Therefore, more practical learning methods capable of speeding up the tuning process are worthy of in-depth exploration.

Conclusion and future work. We have developed a novel self-propelled robotic jellyfish based on the multi-linkage propulsive mechanism and barycenter adjustment mechanism. Unlike conventional jellyfish-like robots performing vertical motions, the incorporated barycenter adjustment mechanism endows the robotic jellyfish with the possibility of 3D attitude regulation. Furthermore, the proposal of a reinforcement learning based attitude control method makes the robotic jellyfish learn a desired attitude in 3D space. Finally, aquatic experiments verify the effectiveness of the presented mechanical design and attitude control method. As is clearly demonstrated, similar to real jellyfish, the self-propelled robotic jellyfish is capable of vertical and horizontal motions, shedding light on the operation of maneuverable jet propulsion.

In the near future, more effort will focus on improving the attitude control method and the propulsive efficiency of the robotic jellyfish. Particularly, the 3D dynamic analysis, modeling, and verification of jellyfish motions will be explored to aid precise estimation of propulsive performance.

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References

1 Wu Z X, Yu J Z, Su Z S, et al. Towards an *Esox lucius* inspired multimodal robotic fish. Sci China Inf Sci, 2015, 58: 052203
2 Liu J C, Wu Z X, Yu J Z, et al. Sliding mode fuzzy control-based path-following control for a dolphin robot. Sci China Inf Sci, 2018, 61: 024201
3 Gemmell B J, Costello J H, Colin S P, et al. Passive energy recapture in jellyfish contributes to propulsive advantage over other metazoans. Proc Natl Acad Sci USA, 2013, 110: 17904–17909
4 Villanueva A, Smith C, Priya S. A biomimetic robotic jellyfish (Robojelly) actuated by shape memory alloy composite actuators. Bioinspir Biomim, 2011, 6: 036004
5 Yeom S W, Oh I K. A biomimetic jellyfish robot based on ionic polymer metal composite actuators. Smart Mater Struct, 2009, 18: 085002
6 Godaba H, Li J S, Wang Y Z, et al. A soft jellyfish robot driven by a dielectric elastomer actuator. IEEE Robot Autom Lett, 2016, 1: 624–631
7 Sutton R S, Barto A G. Reinforcement Learning: An Introduction. Cambridge: MIT Press, 1998
8 Chen C L, Dong D Y, Li H X, et al. Hybrid MDP based integrated hierarchical Q-learning. Sci China Inf Sci, 2011, 54: 2279–2294
9 Cui R X, Yang C G, Li Y, et al. Adaptive neural network control of AUVs with control input nonlinearities using reinforcement learning. IEEE Trans Syst Man Cybern Syst, 2017, 47: 1019–1029