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Automatic video tracking of Chinese mitten crabs based on the particle filter algorithm using a biologically constrained probe and resampling

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The behavioral patterns of crabs affect the quality and quantity of their production. Currently there are no methods to track behavioral patterns using imaging-based algorithms. This study provides a precise pathway tracking method for the research of the relationship between behavioral patterns of crabs and their living environment. The Particle Filter algorithm is an appropriate framework to handle non-Gaussian movement, the biological constraints are used to decrease the computational complexity and improve the accuracy of tracking the crabs' pathways and a biological probe is utilized to determine the area of movement. Then, this newly determined area replaces the entire image frame as the search space to reduce the complexity of the computation. In the resampling step, a traditional Gaussian particle distribution is substituted by a fusiform particle distribution, which better matches the crab's biological motion patterns, to represent the probability of the crab movement. This strategy allows the crab positions to be covered using fewer particles, which is more accurate for analyzing abrupt motion or long-term stationary situations than traditional particle distributions. To determine the robustness and accuracy of the results, 3000 and 12,000 frames were used, respectively. The coverage ratio and accuracy increased by 28.79% and 5.75%, respectively, compared with the color histogram-based particle filter (CHPF) and by 69.57% and 37.66% compared with the fission bootstrap particle filter (FBPF). The experimental results show that the proposed tracking method is feasible and can be used as an efficient tool to get the pathway of crabs under water.

1. Introduction

Chinese mitten crabs are widely harvested crustaceans in China, with production reaching approximately 650,000 tons in 2010 (FAO, 2010). To increase the quantity and improve the quality of crabs, intensive and automatic aquaculture strategies are needed. However, further improvement in the crab aquaculture is limited by insufficient knowledge of crab behavior. Understanding the relationships between different crab behaviors and water quality factors such as dissolved oxygen (DO) and pH is important (Chen, 2007). Therefore, behavioral analysis methods and tracking platforms are required to analyze the crab activity, aiding researchers determine the relationships between different behaviors and the environmental drivers in the crab water habitat.

With the development of computer vision technology, many researchers have designed various systems to automatically observe, store and analyze animal behaviors based on visual inspection (Zion, 2012). An imaging-based system was built to acquire images to study the behavioral rhythms of crustacean decapods inhabiting depths where the sun light is absent (Menesatti et al. 2009). The results showed that video analysis provides a promising direction for animal behavioral search. Later on, a video solution was presented for assessment of benthic populations and biodiversity due to rhythmic behavior (Aguzzi et al., 2012). Besides, the relationship between animal shape and their genetics can be potential to predict animal behaviors (Costa et al., 2011). Although all aforementioned methods can be used to explore the relationship between animal behaviors and their living environment, they do not estimate the pathway of the animal under water overtime since it is hard to track animal movements using traditional pattern recognition algorithms. However, recently developed video tracking algorithms provide pathway information of tracking objects.

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Video tracking is the method which can obtain the positions of a target of interest (Khan et al., 2005; Veeraraghavan et al., 2008). In the last few decades, video tracking has been widely applied to track pedestrians, cars, and other targets. Generally, these algorithms are divided into two types: the linear (Gaussian, unimodal problems) and the non-linear (non-Gaussian, multimodal problems). Kalman filter has been proven successful in solving linear problems, and uses a series of measurements of observed overtime to estimate the status of the object in the future (Crisan and Doucet, 2002). However, its performance is reduced in non-linear situations. It is not suitable for tracking animals because movement of animals is typically non-linear. Researchers have presented various strategies, such as the extended Kalman filter (EKF), the unscented Kalman filter (UKF), and the particle filter (PF), among others, to correctly track objects in non-linear situation (Cheng and Zhang, 2008).

With advances in computational ability, the particle filter (Gordon et al., 1993) has been deemed an efficient model for a non-linear, non-Gaussian and multi-model state space. The particle filter algorithm is based on a sequential Monte Carlo method, so the importance sampling (IS), and the sequential importance sampling (SIS) are two critical factors of the particle filter algorithm. However, the simple SIS was used in all these particle filter algorithms, causing a degeneracy problem after several iterations (Chen, 2003). Gordon et al. proposed the landmark method termed the bootstrap particle filter (BPF), a novel resampling strategy that is based on utilizing the SIS to solve the degeneracy problem, which, in turn, causes the problem of sample impoverishment (Gordon et al., 1993). According to Gordon, many novel resampling strategies such as the Markov Chain Monte Carlo (MCMC) shifting (Khan et al., 2005), Kernel smoothing (Arulampalam et al., 2002), regularization (Cheng and Zhang, 2008), and fission BPF (Punskaya et al., 2001) have been presented. Recently, Han et al. utilized the immune genetic algorithm (IGA) to increase the number of meaningful particles to remedy the sample impoverishment and ensure diversity in the particle set (Han et al., 2011).

In addition to the resampling strategy, the transition is another crucial part of the particle filter. Some researchers redirected their methods to find variety and ensure a correct transition. Yan et al. presented a particle filter using scale-invariant feature transform (SIFT) to enhance their accuracy and robustness (Yan et al., 2011). Along with the development of object detection procedures (Felzenszwalb and Huttenlocher, 2004; Liu et al., 2011; Alexe et al., 2012), a joint detection and particle filter method to track colored objects was proposed (Czyz et al., 2007), making two distinct contributions: (1) target detection and deletion are embedded in the particle filter without relying on an external track initialization and cancellation algorithm; and (2) the algorithm is able to track multiple objects that share the same color description while maintaining the attractive properties of the original color particle filter.

To examine the tracking abilities of these animal behavior analysis systems based on computer vision, two premises are adopted: (1) The particle filter is an efficient way to track an animal's motion due to its prominent effect on non-linear, non-Gaussian and multi-modal cases, which occur frequently in nature; and (2) the basis of the particle filter is an effective and robust sample (transition) or resampling strategy.

The overall objective of this paper is to address the issue of accurate tracking of the pathway of the crab movement under water. To achieve the objective, a 2-D imaging system was constructed to acquire video sequences of crabs under water, and a biologically constrained based particle filter (BCPF) was applied to obtain the position of crabs on a frame by frame basis, thus providing the pathway of the crab overtime. Moreover, the BCPF capability was extended to mitigate the tracking shifts caused by abrupt movement and/or extended stationary periods of crabs, and reduce the tracking errors accumulated in each particle matching iteration.

2. Materials and methods

2.1. Chinese mitten crab behavioral analysis platform

An automated Chinese mitten crab behavioral analysis platform based on 2-D computer vision technology was designed consisting of five parts, including an enclosed box, a fluorescent lamp (T5HO 47W, GE Lighting, U.S.), a water tank, a water-cycling device (HW303B, Sunsun Corporation, P.R. China), a CCD (DH-HV3151UC, Daheng Imaging Corporation, P.R. China) color camera, and a host computer (Fig. 1). The enclosed box blocks out any external interference, such as luminance or noise. The fluorescent lamps boost the lighting conditions to improve the quality of the video sequences captured in our artificially closed environment. The water-cycling device ensures the water purity and keeps the water temperature stable.

A CCD color camera is positioned on the top of the water tank to acquire video data. The data are transmitted to the host computer through a USB interface. The host computer used for image processing was built around an Intel Core i5 CPU with a 2.8 GHz processor and 4 GB of RAM, running Windows 7 Service Pack 1 (SP1) with Visual Studio 2010. The Open CV 2.4 library is utilized as the video processing framework.

2.2. Video acquisition

Our study monitored Chinese mitten crabs obtained from Yixing, Jiangsu Province, which is one of the main breeding areas in China. More than 33 h of video sequences used in the experiment were captured by the CCD color camera with a frame resolution of 720 $\times$ 540 at 20 frames per second (fps). To capture high-quality video sequences, the water in the tank was approximately 10 cm depth, with the bottom of the tank covered by white marble sand to create uniform background thus eliminate problems caused by shadow or reflection of the glass materials and background complexity. Each video contains the motions of four mature crabs (Fig. 2), however the BCPF was applied to motions of individual crabs, because multiple object tracking is beyond the scope of research presented herein.

2.3. Dynamic model for crab tracking

Crab video tracking is regarded as a Bayesian estimation problem and a representative dynamic state model needs to be defined prior processing the video data. The crab shell is used to represent the entire crab, which means that claws and legs are ignored during the tracking.

Eq. (1) represents the state vector of a single crab in the non-linear dynamic state space:

$$X_t = [x_t, y_t, W_t, H_t] \tag{1}$$

in which t denotes the frame number. The term (x_t, y_t) denotes the middle point coordinate of the target region (rectangle in ourcase) in which the target's color histogram and object template are computed. The terms W_t and H_t denote the width and height of the track region, respectively. The particles are predicted in accordance with the second-order autoregressive dynamics of a random walk as shown by Eq. (2):

$$X_t = A_0 \times (X_{t-1} - X_0) + A_1 \times (X_{t-2} - X_0) + X_0 + B \times w_t \tag{2}$$

in which X_0 represents the initial state of the crab tracker A_0, A_1, and B are the coefficients defined by 2.0, −1.0, and 1.0, respectively; and