Robotic Detection and Tracking of Crown-of-Thorns Starfish

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Abstract—This paper presents a novel vision-based underwater robotic system for the identification and control of Crown-Of-Thorns starfish (COTS) in coral reef environments. COTS have been identified as one of the most significant threats to Australia’s Great Barrier Reef. These starfish literally eat coral, impacting large areas of reef and the marine ecosystem that depends on it. Evidence has suggested that land-based nutrient runoff has accelerated recent outbreaks of COTS requiring extensive use of divers to manually inject biological agents into the starfish in an attempt to control population numbers. Facilitating this control program using robotics is the goal of our research. In this paper we introduce a vision-based COTS detection and tracking system based on a Random Forest Classifier (RFC) trained on images from underwater footage. To track COTS with a moving camera, we embed the RFC in a particle filter detector and tracker where the predicted class probability of the RFC is used as an observation probability to weight the particles, and we use a sparse optical flow estimation for the prediction step of the filter. The system is experimentally evaluated in a realistic laboratory setup using a robotic arm that moves a camera at different speeds and heights over a range of real-size images of COTS in a reef environment.

I. INTRODUCTION

Crown-Of-Thorns Starfish (Acanthaster planci) are identified as one of the most significant threats to Australia’s Great Barrier Reef. These starfish literally eat the coral. It is estimated that starfish and cyclones, combined, contribute to destruction of over 50% of the coral in the Great Barrier Reef [1]. The recovery time for the reef is substantial and the Crown-Of-Thorns Starfish (COTS) have few natural predators. Whilst COTS are found naturally in the reef, since the 1960’s, evidence suggests that nutrient runoff from farmland and urban development has accelerated outbreaks of COTS [2]. Figure 1 shows examples of COTS and the rapid and extensive damage they cause to reef (white scars on eaten coral) when in large numbers.

The current best method for controlling COTS1 when in outbreak numbers (approximately 30 per hectare) is manual injection of a biological agent into the starfish by a diver using a hand-held supply gun and needle [3]. Divers perform coverage of infested areas and use hand-eye coordination to apply the end of the 1m long applicator to the body of the COTS. During multi-diver surveys, the starfish are typically flipped over using a hook to indicate to other divers that the COTS has been injected. Divers also record limited information, such as the number of injected COTS, which is used to monitor the efficiency of the campaign. However, the use of divers makes this form of control extremely expensive (personnel and surface vessel time), and introduces significant safety concerns limiting dive time and restricting work to daylight hours and calm sea conditions.

A robotic system capable of COTS control has a number of merits. It firstly eliminates the costs and risks associated with using human divers. A robot could operate day and night,
and at beyond human dive depth, and is relatively immune to sea surface conditions. Secondly, a robot could localise itself with respect to the underwater terrain and precisely record the location of every COTS sighted and/or treated, along with detailed metadata such as depth, water temperature, light levels and terrain structural complexity. Such information could be exchanged between multiple robots to ensure effective coverage without duplicate treatments. It can also be used by marine scientists to assist with modelling population dynamics and designing effective monitoring and management programs.

Achieving robotic control of COTS population numbers requires three critical technologies:

1) An effective means of treating COTS: Guidelines have been developed by the Great Barrier Reef Marine Park Authority [3] and has been proven in diver-based COTS eradication campaigns.

2) A capable underwater platform that can be used by non-technologists: Guided by previously Autonomous Underwater Vehicle (AUV) technology [4], [5], a vehicle will be developed and fitted with a simple robotic arm and injection system and use vision-based control [6] to coordinate motion of the arm and vehicle relative to the COTS. Figure 2 illustrates a concept AUV and injection system proposed for COTS control.

3) Robust image-based classification of COTS: The focus and contribution of this paper.

The overall contribution of this paper is a highly robust vision-based classifier — the key technology for robotics COTS control — which we experimentally validate under controlled conditions. The specific novel contributions are threefold: (1) We propose a random-forest based classifier exhibiting very high precision in detecting COTS. (2) We embed the classifier in a particle filter tracker which is capable of robust tracking of COTS in an image sequence from a moving camera. (3) We use a hardware simulator where a Baxter robot’s hand camera models an underwater vehicle as it moves over large-scale images of complex coral reef environments containing COTS.

The remainder of the paper is structured as follows: Section II discusses the related work with Section III presenting our proposed COTS image-based detection system. Section IV describes the experimental evaluation and the results. Finally, Section V draws conclusions and discusses future research.

II. RELATED WORK

Historically, biological studies of marine life and terrain, which use underwater image data, are performed manually. This includes labelling and mapping of the objects of interest such as corals [7]. This is due to the challenging conditions that underwater environments impose on the quality of the captured optical data and the structural complexity of the scene. Early attempts to automate the process of classifying different corals can be found in [8], [9]. In these studies, color and texture-based features were extracted from close-up images to perform a whole image classification into different benthic substrate categories.

In recent years, a considerable body of work relating to image-based marine benthic habitat classification using images collected by robotic systems has emerged [10], [11]. There is however a paucity of any research relating to image-based underwater fauna classification. Most works consider automated fish counting using stationary monocular and stereo image sequences [12]. Only few works have considered starfish detection, with shape-based features used for the detection of starfish that live on the sandy seafloor [13], [14]. However this is not representative of the complex environment where COTS are found.

Currently, there is only one paper that describes the detection and monitoring of COTS from underwater imagery [15]. The approach uses a template-based detection method based on Local Binary Patterns (LBP) [16] and showed that LBP is a powerful technique to use for COTS detection. It also highlighted that improved classification performance could be achieved with constant altitude imagery as can be collected by underwater robots.

In this work, our aim is to detect COTS from a moving underwater robot then provide tracking information to the robot’s arm to inject the COTS. In the computer vision literature, object tracking is usually achieved with a template-based [17] approach or through a learning-based approach [18]. The template-based approach is suitable for 2D objects that experience small affine transformations. However, it performs poorly when there is a large change of view point, such as in complex reef environments.
Tracking-by-detection [19] is an example of a learning-based approach for tracking. There are many varieties of this method but all follow the same general procedure, i.e. continuously applying a detection algorithm for each individual frame while at the same time performing data association across frames. However, these methods suffer robustness issues due to typical detectors being prone to misclassification and thus tend to miss detection in some frames altogether. In order to address this problem, various authors [20], [19] proposed the use of a Markovian framework to track the uncertainty in the detection and provide robust tracking. Our proposed approach follows a similar idea.

III. Approach

The aim of this research is to robustly detect COTS within complex reef environments with a moving monocular camera, and track a fixed point on its body so an injection can be administered. In order to achieve this we propose the novel combination of a Random Forests Classifier (RFC) [21] and a Particle filter [22]. The RFC is trained on manually selected data from a range of underwater imagery and video of COTS taken by marine scientists and recreational divers. We propose the use of the predicted class probability from the RFC as an observation measurement for updating the particle filter. The prediction step of the particle filter uses sparse optical flow to propagate the particles as described in Section. III-C. The following section details the image features used for the RFC training dataset.

A. Features

COTS are moving non-rigid organisms that can be extremely difficult to detect, even for divers. Therefore, any image-based detection system requires a set of robust features to facilitate detection and segmentation. Shape and color are often strong descriptors for animals. Whilst COTS have a starfish like pattern when on flat terrain (see Fig. 1(a)), it is more typical for them to conform to (wrap around) and even partially hide within coral making overall shape-based detection unreliable. The color of COTS varies considerably depending on their age, location and viewing altitude, giving inconsistent performance in image-based detection [15].

A distinctive feature of COTS is their thorns. This characteristic lends itself to texture-based features for detection. However, using texture alone is not sufficient for reliable classification due to COTS living on different types of reef structure (corals) that can exhibit similar texture to the COTS. Therefore, additional information is required to improve robustness. The long thorns of the COTS often give a strong edge response in their images; hence, a feature that captures the edge information would be ideal. Based on this, we chose to use a feature vector that combines Local Binary Patterns (LBP) [23] for the texture and Histogram of Oriented Gradient (HoG) [24] for the edge responses.

1) Local Binary Patterns (LBP): This common image operator was first introduced in [16] and can be expressed in its simplest form as:

$$LBP(c) = \sum_{n=1}^{8} 2^n s(i_n - i_c)$$

where \(n\) iterates over the eight pixel neighbours of the central pixel \(c\) in a \(3\times3\) neighbourhood. \(i_c\) and \(i_n\) are intensity values of the pixels. \(s(x)\) is 1 if \(x \geq 0\) and 0 otherwise.

In this work, we use the extended version of LBP, called “uniform patterns”, introduced in [23] which makes the feature descriptors grayscale and rotation invariant. In order to create an image descriptor using this operator, the image is equally divided into non-overlapping sub-regions of radius \(r\) containing \(M\) discrete circular sample points, and a LBP histogram computed for each sub-region based on the comparison of the intensity of the centre pixel and the sample points. In our case, the LBP histogram is calculated from \(100 \times 100\) pixel sub-regions with a radius of \(r = 3\) and \(M = 24\) resulting in a histogram of 26 bins.

2) Histogram of Oriented Gradient (HoG): Originally introduced by Dalal and Triggs [24], this feature is widely used for object detection and tracking. This feature is computed by firstly dividing the detection window into cells with equal size. For each cell, a histogram is created from a weighted vote by each pixel based on the magnitude and orientation of its intensity gradient. In our case, the detection window is \(100 \times 100\) pixels containing one cell and the histogram has 6 bins which are evenly spread over 0 to 180 degrees.

The 26 LBP and 6 HoG histogram bins are concatenated to form a 32 element feature vector for the sub-region used for classification.

B. Random Forests classifier (RFC)

RFC [21] is an ensemble of decision trees, created by bootstrap samples of the training data. An RFC utilises random feature selection process for the tree induction process. Prediction is made by aggregating (majority vote for classification or averaging for regression) the predictions of the forest. The output class probability of this classifier

![Fig. 3: Samples of images from our COTS dataset. The dataset contains 3157 images and it is used for training of a Random Forest Classifier. Top row: positive samples. Bottom row: negative samples.](image)
is computed as the mean predicted class probabilities of the trees in the forest. The classifier is trained using the LBP-HOG feature vector of length 32 as described above. The training is done using 5-fold cross-validation [25] with parameter grid-search to find the best parameters. The cross-validation procedure is used in order to avoid over-fitting. Using the best parameters, the classifier is then trained on the whole training set. The RFC is trained on the following described dataset.

1) Dataset: A dataset was developed containing 3157 small images, each of 100 × 100 pixels, of COTS and non-COTS examples. These images were manually collected from publicly available YouTube footage of COTS captured by recreational and scientific divers. The dataset images range from capturing the full COTS to only capturing a close-up view of one of their arms. The dataset images are captured in the natural habitat of the COTS and reflects the real-environment conditions including the visibility constraint. The dataset is split between 30% positive examples and 70% negatives, see Fig. 3 for a sample of the images in the dataset. We created the dataset using a false positive mining technique as follows: (1) We started with a dataset containing a few hundred images and trained an RFC which has a low accuracy. (2) This classifier is then applied to new (unseen) images and we collect the strong false positives and the weak true positives based on the probability score provided by the random forest. (3) This new data is then labelled correctly and added to the dataset. (4) The process is repeated by re-training the RFC on the new, now bigger, dataset. (Please note that during training, the classifier never saw any samples taken from the images used for the experimental evaluation presented in Section IV).

C. Particle Filter (PF)

A Particle Filter (PF) was developed here to improve tracking of COTS as the camera moves over the scene. Particle filtering estimates a system state \( x_t \) sequentially — each iteration consists of a prediction step based on a motion model and an update step based on measurements [22]. The prediction step estimates the current distribution given all prior observations, \( z_{1:t-1} \):

\[
p(x_t|z_{1:t-1}) = \int p(x_t|x_{t-1})p(x_{t-1}|z_{1:t-1})dx_{t-1}. \tag{2}
\]

\( p(x_t|x_{t-1}) \) represents the state transition and can be estimated using a motion model:

\[ x_t = f_t(x_{t-1}, \nu_t), \tag{3} \]

where \( \nu_t \) is the process noise.

The update step estimates the posterior distribution given the new observation \( z_t \):

\[
p(x_t|z_{1:t}) = \frac{p(z_t|x_t)p(x_t|z_{1:t-1})}{p(z_t|z_{1:t-1})}. \tag{4}
\]

\( p(z_t|x_t) \) represents the observation density and can be estimated using a measurement model:

\[ z_t = h_t(x_t, \omega_t), \tag{5} \]

where \( \omega_t \) is the measurement noise.

In our case, the state, \( x = [u \ v]^T \), is the image-plane coordinate of a fixed point on COTS. The objective of a PF tracker is to approximate the posterior distribution \( P(x_t|z_{1:t}) \). The approximation is done using a set of \( N \) particles, \( \{x^i_t\}_{i=1}^N \) with importance weights \( \{w^i_t\}_{i=1}^N \). Each particle represents the centre of a 100 × 100 pixel window in the image. The prediction and update steps used here are:

1) Predict: Apply the motion model to propagate each particle, \( \{x^i_t\}_{i=1}^N \). In our case, the positions of the particles are propagated by calculating the flow velocities in two consecutive frames using Lucas-Kanade optical flow method [26] for the particle with the largest weight.

2) Update: Evaluate the weight for each particle using the observation density: \( w^i_t = p(z_t|x^i_t) \) and then normalize. In our case, \( p(z_t|x^i_t) \) is the predicted COTS probability from the RFC at the particle, \( x^i_t \).

The proposed PF used in this work has three modes:

1) Searching for a COTS in the current view: In this mode the particles are kept in an initialisation stage. That is, the particles are initialised based on a uniform distribution and the weights are calculated for each particle based on the RFC predicted probability. As long as the RFC did not detect a COTS at the position of any particle, the step is repeated in the next frame. By re-initialising the particles, the detector examines different areas in the field-of-view of the robot.

2) Tracking: As soon as the RFC detects a COTS at any particle position, the initialisation stage is stopped and the tracking begins. As mentioned above, a sparse optical flow estimation is used for the prediction step of the particle filter and then the weights of the particles are updated based on the RFC predicted probability. If the COTS stay in the view of the robot, the particles will begin to converge.

3) COTS lock-on: As soon as the norm of the covariance matrix of the particle positions is below a certain threshold, the best particle is used as a seed for a sparse optical flow tracker that provides smooth tracking of a fixed point on the COTS body. This is important for future work where visual servoing will be performed to administer the injection. As soon as the RFC predicted probability for the best particle drop below certain threshold, the COTS considered out of view and the system is reset back to the search mode.

The supplementary video to this paper shows the results of the particle filter approach applied to the detecting and tracking.

IV. EXPERIMENTS AND RESULTS

An experimental evaluation of the approach described in Section III-C was conducted using a Baxter robot controlling a camera over reef environment scenes containing COTS and no COTS. First, we present the results of the RFC on the dataset. Then, the performance of the entire approach with varying camera speed and altitude across the images is presented.
A. Performance of the RFC on the dataset

Although the LBP is rotationally invariant, the combined LBP-HOG feature vector is not. Therefore, to introduce a degree of rotational invariance, each image in the dataset was rotated 90°, 180° and 270° resulting in a combined $12028 \times 32$ labelled features to train and test the RFC.

To test the classification systems, we first split the labelled features into two sets: (1) a training set from 80% of the data, and (2) a test set from the remaining 20%. Using the training set, we employed a 5-fold cross-validation training procedure, i.e. we randomly split the data into 5 parts and systematically used each part once for testing and the rest for training. To measure the accuracy of the RFC, we use the F1-score (Eq.6) on the 20% test set:

$$F1\text{-score} = \frac{2 \times (\text{precision} \times \text{recall})}{(\text{precision} + \text{recall})}$$

Table I presents the recall and precision for both COTS and No-COTS class in the test set along with the F1-score. By adjusting the decision threshold from 0.5 (the predicted class probability used in Table I) to 0.68, we can achieve 100% precision at 80% recall. Precision is important in our application as false positives could lead to the robot attempting to inject coral instead of the COTS and damaging the applicator.

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<th></th>
<th>precision</th>
<th>recall</th>
<th>F1-score</th>
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<td>0.99</td>
<td>0.98</td>
</tr>
<tr>
<td>COTS</td>
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B. Performance of the detection system based on height and speed

An experimental evaluation of the proposed classification and tracking scheme was conducted using a Baxter robot to move a camera to simulate an AUV surveying within a reef environment (Fig. 4). Baxter is a robot that has two arms, each with 7-degrees of freedom and equipped with cameras on its head and both of its hands. The camera in its left hand was used for these experiments.

A set of 5 high-resolution images taken of COTS in different reef environments were printed as posters (112 cm×84 cm in size), see Fig. 7. The poster dimensions made the size of the COTS similar to their actual size. Note that one of the posters does not contain any COTS.

To systematically evaluate the algorithms, each poster was laid flat on a table and using the left hand of the Baxter robot, shown in Figure 4, the posters were scanned by the hand following a fixed trajectory. The actual trajectory, designed to replicate a high-density coverage survey, is illustrated on one of the posters as seen in Fig. 5. Fig. 6 shows an example image taken from Baxter’s camera at the beginning of one of the transects.

To replicate different survey conditions, the trajectory was conducted with five different speeds and three heights...
Fig. 7: The baseline images of COTS in different reef environments and visibility conditions used for the experimental evaluation. The images were printed as 112 cm × 84 cm posters. Posters are labelled 1 to 5 clockwise from top left.

Fig. 8: Three views of the same COTS from three different heights (left 108 mm, middle 208 mm, right 338 mm).

resulting in 15 different sequences of images per poster (75 in total). The speeds of the camera over ground tested were 0.03, 0.04, 0.09, 0.1 and 0.2 m/s, and these were repeated at altitudes of 108, 208 and 338 mm above the scene. Fig. 8 shows a view of the same COTS from the three different heights.

The images were captured at 4 Hz with a resolution of 640 × 400 pixels, (please note that this limit is based on the hardware used and a much higher frame rate can be achieved on a better CPU). The number of particles used for this experiment is 35 where each particle covers a 100 × 100 pixel window.

For each sequence, all the images that have a particle with a corresponding RFC predicted probability greater or equal to 0.5 was saved to disk. Using the saved images, we have calculated the precision of the system based on Eq. 7:

$$\text{precision} = \frac{\text{true positives}}{\text{true positives} + \text{false positive}}$$ (7)

Table II summarises all the classification results from the five posters for each of the five speeds and three heights. Fig. 9 shows the average precision across all posters for each different combination of height and speed. As can be seen, increasing the speed of the camera over the scene reduced the precision. This is due to increased motion blur, particularly as the altitude decreased. Another influence on the precision was the altitude. As altitude decreased, the reduction of texture in the sample image decreased the precision. Note that for the above results we counted all the images that contains at least one particle with RFC probability above or equal 0.5, however, during deployment and as described in section III-C, the tracker needs to reach a lock-on stage.

Fig. 9: The detector average precision for different speeds and ranges of the robotic arm.
before a detection is considered which increases the precision to 100%. The supplementary video shows the particle filter approach applied to the detecting and tracking.

V. CONCLUSIONS AND FUTURE WORK

Crown-Of-Thorns Starfish (COTS) are severely impacting Australia’s Great Barrier Reef and the marine ecosystem that it supports. Current methods for controlling COTS numbers employing divers are operationally expensive and logistically difficult. Here we have introduced a novel vision-based classification system for application on an Autonomous Underwater Vehicle equipped with a robotic injection system for controlling COTS numbers within reef environments. The precise classifier is robust with respect to camera motion and complex textured scenes. The detection method is based on a Random Forest Classifier (RFC), trained on images from underwater footage. To enable real-time operation, and take advantage of the temporal aspect of the camera stream, we developed a particle filter detector and tracker that uses the score of the RFC as a measurement to weight the particles and a sparse optical flow estimation for the prediction step of the particle filter. The system was evaluated using a laboratory robotic arm that moves a camera, at different speeds and heights, over various real-size images of COTS in a reef environment. The results demonstrate the robustness of the algorithms in visual detection of the COTS. Future work is focused on extending the algorithms to discriminate individual COTS when in mass aggregation as illustrated in Figure 1, and on transferring the algorithms to an AUV for in-situ reef trials.

ACKNOWLEDGMENTS

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REFERENCES


TABLE II: Summary of all the classification results from the five posters for each of the five speeds and three heights. Fig. 9 summarises these numbers as average precision for all speeds and heights over all the COTS posters (without the one with No-COTS). (FP: false positives. TP: true positives)

Height = 108mm

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<td>FP</td>
<td>TP</td>
<td>TP</td>
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<td>6</td>
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<td>10</td>
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<td>6</td>
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