Detecting, Tracking and Counting Fish in Low Quality Unconstrained Underwater Videos

DETECTING ,TRACKING AND COUNTING FISH IN LOW QUALITY UNCONSTRAINED UNDERWATER VIDEOS

Concetto Spampinato
Department of Informatics and Telecommunication Engineering, University of Catania, Catania, Italy
cspampin@diit.unict.it

Yun-Heh Chen-Burger , Gayathri Nadarajan, Robert B. Fisher,
School of Informatics, University of Edinburgh, Edinburgh, UK
jessicac@inf.ed.ac.uk, gaya.n@ed.ac.uk, rbf@inf.ed.ac.uk

Keywords: Motion Detection, Tracking, Fish Image Processing, under-water marine life observation.

Abstract: In this work a machine vision system capable of analysing underwater videos for detecting, tracking and counting fish is presented. The real-time videos, collected near the Ken-Ding sub-tropical coral reef waters are managed by EcoGrid, Taiwan and are barely analysed by marine biologists. The video processing system consists of three subsystems: the video texture analysis, fish detection and tracking modules. Fish detection is based on two algorithms computed independently, whose results are combined in order to obtain a more accurate outcome. The tracking was carried out by the application of the CamShift algorithm that enables the tracking of objects whose numbers may vary over time. Unlike existing fish-counting methods, our approach provides a reliable method in which the fish number is computed in unconstrained environments and under several scenarios (murky water, algae on camera lens, moving plants, low contrast, etc.). The proposed approach was tested with 20 underwater videos, achieving an overall accuracy as high as 85%.

1 INTRODUCTION

Traditionally, marine biologists determine the existence and quantities of different types of fish using several methods, including casting nets in the ocean for collecting and examining fish, human underwater observation and photography (Rouse 2007, Schlieper 1972), combined net casting and acoustic (sonar) (Brehmera et. al, 2006) and, more recently, human hand-held video filming.

Each of such methods has their drawbacks. For instance, although the net-casting method is accurate, it kills the collected fish, damages their habitat and costs much time and resources. Human manned photography and video-making but do not damage observed fish or their habitat, the collected samples are scarce or limited and is intrusive to the observed environment therefore do not capture normal fish behaviours.

This paper presents an alternative approach by using an automated Video Processing (VP) system that analyses videos to identify interesting features. These videos are taken automatically and continuously by underwater video-surveillance cameras near the Ken-Ding Taiwan sub-tropical coral reef waters. The video collection was produced as a part of the on-going efforts of the Taiwanese EcoGrid project (*http://ecogrid.nchc.org.tw*).

The proposed automated video processing system is able to handle large amount of videos automatically and speedily gives those un-watched video clips a chance to be analysed. The system's performance is promising, as shall be reported later on in this paper.

The challenges that differentiate the undertaken work as reported here when compared with other traditional methods are in the nature of the videos to be processed. Traditionally, such tasks only deal with videos taken in a controlled environment or a lab, e.g. a fish tank with fixed lighting, cameras, background, fixed objects in the water, known types of fish, etc. Based on these pre-determined conditions, the VP software can be gradually tuned to suit this fixed environment and gains better performance over time.

This condition, however, was not possible in our case, as our videos were taken in an un-controlled open sea where the degree of luminosity and water flow may vary depending upon the weather and the time of the day. The water may also have varying degrees of clearness and cleanness. Moreover, unlike a normal fish tank in a lab, open sea videos will consist of "non-fish" moving objects – which require additional handling to eliminate. In addition, as algae grow rapidly in subtropical waters and on camera lens, it affects the quality of the videos taken. Consequently, different degrees of greenish and bluish videos are produced. In order to decrease the algae, frequent and manual cleaning of the lens is required.

The next session introduces our three Image Processing (IP) Tasks, which is followed by a description of our texture and colour analysis subsystem. The fish detection and tracking systems are then described followed by an analysis of their performance. We report an 85.72% overall success rate over 20 movies (about 8000 frames) when comparing with a current state of the art, e.g in (Morais et al, 2005) 81% success rate, that operates on video clips shot in a controlled environment.

2 IMAGE PROCESSING TASKS

Currently, marine biologists manually analyse underwater videos to find useful information. This procedure requires a lot of time and human concentration, as an operational camera will generate imagery data of about 2 Terabytes (20 millions frames) per year. Moreover, most of such analyses are done un-aided by VP/IP software. For one minute's video, it will take a human about 15 minutes for classification and annotation. To fully analyse existing videos alone, generated by the three underwater cameras over the past four years, will take human approximately 180 years.

The proposed system therefore aims to support the non-VP trained users to leverage VP and IP software to help their normal line of work.

Given an underwater video, our system analyses it and provides relevant information, e.g. the number of fish present, quality of the video (clear, murky, smoothed, etc), dominant colour of the video. To provide such information, the developed video processing system consists of three main image processing subsystems: Texture and Colour Analysis, Fish Detection, and Fish Tracking.

The output of our VP system is provided both by displaying the coarse-grained results directly onto the video and in elaborated, ontologically grounded Prolog predicates in a text file.

Figure 1 illustrates the classification information generated by the system as displayed in a video: *Medium, Clear, Fishes, Not Green*. They represent the average luminosity, the average smoothness, the presence (or non-presence) of fish and the green-toned quality of the frame. The top left number (2) indicates the numbers of fish in the frame and the lower left number (6) indicates the total numbers of fish in the whole video. The two square boxes surround fish identified by the system. Most of the annotations are given in plain natural language (medium, clear, etc) for a better understanding for non-image processing people like the marine biologists.

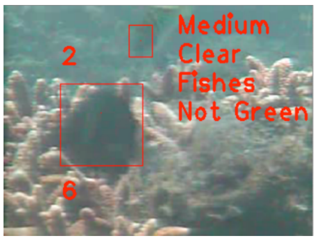


Figure 1: Annotations as displayed in a processed video

3 TEXTURE AND COLOUR ANALYSIS SYSTEM

The aim of this subsystem is to detect the average texture and colour properties of each frame. The evaluated properties are: 1) ***Brightness***: classified in *Dark/Medium/ Bright*; 2) ***Smoothness***: classified in *Blur/Clear*; 3) ***Colour***: identification of green colour tone, classified in *Green/Not Green;* ***Hue, Saturation and Value***: classified in *High/Medium/Low.*

The approach used for describing the image texture (e.g. brightness and smoothness) is based on analysing the statistical moments of the grey-level histogram. Let z be a random variable denoting image grey levels and $p(z_i)$ i=1,2, …., L-1 be the corresponding histogram, here L represents the distinct grey levels. $p(z_i)$, i=1…N is the normalized histogram, so that $\sum_{i=1}^{N} p(z_i) = 1$.

The nth moment of the grey level histogram of an image is therefore:

$$\mu_n(z) = \sum_{i=0}^{L-1} (z_i - m)^n \cdot p(z_i) \quad (1) \qquad m = \sum_{i=0}^{L-1} (z_i) \cdot p(z_i)$$

Where m is the mean value of z (the average grey level). The variance is the second order momentum μ_2. The third order moment μ_3 is a measure of the skewness of the histogram, while the fourth order moment μ_4 is a measure of its relative flatness.

Other measures that we use are the uniformity U and the entropy E:

$$U = \sum_{i=0}^{L-1} p^2(z_i) \quad (2) \qquad E = -\sum_{i=0}^{L-1} p(z_i) \cdot \log_2 p(z_i) \quad (3)$$

In particular, for constant images $U = 1$ and $E = 0$. Using these values, we can estimate the brightness (formula 4) and the smoothness (formula 5) characteristics.

$$r_{bright} = m + \frac{\mu_3(z) \cdot 255^2}{k} \quad (4)$$

$$r_{smooth} = \left(\frac{1}{\mu_2(z)} + \frac{1}{\mu_4(z)} + E \right) \cdot U \quad (5)$$

Where k is constant, usually set to 10. If r_{bright} of a video is found to be larger than a pre-determined threshold, we classify this video as "Bright". Similarly, we use r_{smooth} and its corresponding threshold to determine the smoothness of a video. For colour analysis, we extract the Hue, Saturation and Value planes. For each plane, we compute the averaged percentage of the pixels whose value is larger than a suitable threshold in the video.

To determine whether a video is *Green colour toned* or not, we determine the green plane of a frame and then we count all the pixels in such plane which value is greater than 128. Nextly we aggregate those values to decide the overall green colour tone of the video. These results are stored in relevant Prolog predicates.

Sample images of real videos captured in the sea are provided in Figure 2, with the machine-generated annotation displayed on them.

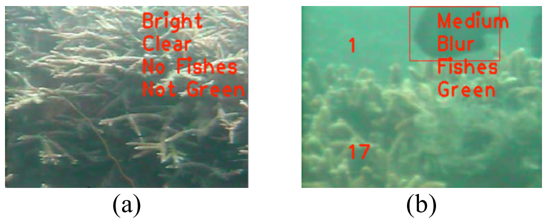


Figure 2: Example classified video results

The classification task was done on all 20 videos, using the texture and colour analysis subsystem.

Table 1 shows the obtained results for the texture analysis, where *NV* indicates the number of videos that weren't correctly classified, *PV* the number of videos correctly classified and *CSR* the success rate for each analysed feature.

Table 1: Classification Results

Feature	NV	PV	% CSR
Smoothness	1	19	95%
Brighteness	1	19	95%
Colour	2	18	90%

4 FISH DETECTION SYSTEM

One piece of useful information for marine biologists is the number of fish present in a video, which can help them identify promising videos. Object detection is therefore needed.

The main difficulty encountered was the choice of the fish detection algorithm, which has the fundamental influence on the performance of the tracking and counting systems. Given the main constraint of fast processing over the large amount of video data, most of the algorithms explored were based on subtracting a reference image, representing the background, from the current input image.

Before selecting the moving average algorithm, we considered several algorithms (the Gaussian Model (Rajagopalan et al, 1999) and the H-Model (Faro et. al., 2004)) that avoided the computationally expensive background updating step, based on the use of morphological and spatial filters.

The main shortcoming of these algorithms were the large processing time and the difficulty of choosing a generally applicable sequence of filters and parameters. Therefore, a moving average algorithm was selected, because it gave a good balance between processing time and accuracy over the static scenarios.

So let CB and FR_n be background image and nth frame, respectively. Then the moving pixels of frame n, MP_n, are detected by:

$$MP_n(x, y) = \begin{cases} \longrightarrow if \left| CB(x,y) - FR_n(x,y) \right| > T_n \\ \longrightarrow else \end{cases} \quad (6)$$

where *Tn* is computed based on (Otsu, 1979). To model CB for gradually evolving scenes, we use the adaptive background update method, where CB is given by the following formula:

$$CB_n(x,y) = (1-\alpha) \cdot CB_{n-1}(x,y) + \alpha \cdot FR_n(x,y) \quad (7)$$

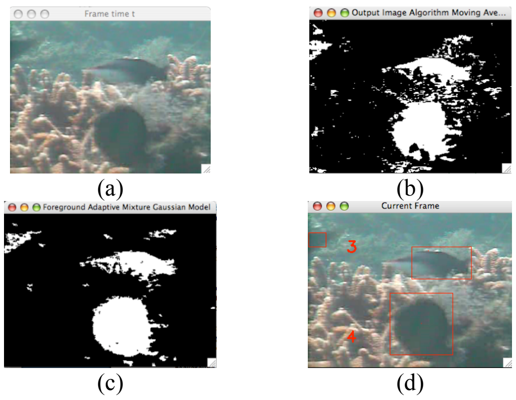
where α (alpha) regulates update speed (how fast an accumulator forgets about previous frames). This update occurs only for background pixels. Figure 3(b) shows such an example.

Unfortunately, this algorithm does not handle well outdoor scenes where the background is not completely static but containing tree, algae or bush motion. For this reason, we added an algorithm which removes many of the false positives (arising from moving objects) generated by the moving average algorithm. Algorithms were explored that were based on dynamically estimating the background. Many of them require an accurate calibration phase and rely on a careful selection of critical parameters, as for example an algorithm based on Kalman filtering. Alternatively, the algorithms were too slow.

The algorithm chosen was the Adaptive Gaussian Mixture Model (Zivkovic, 2004), which was reliable enough for removing the false positives and fast enough. In this algorithm, each background pixel is modeled as a mixture of Gaussians. Afterwards, each pixel is classified based on the likelihood that the observed pixel value is explained by the gaussian mixture model. Figure 3(c) shows the output of this new algorithm.

If it was used independently, it may fail when slowly moving objects are present in the scene. The moving average detection algorithm, on the other hand, overcomes such problems.

Therefore, a combination of these two algorithms gave a reliable solution for fish detection, as each algorithm solves some problems of the other. Therefore, let AP_n be the output image of the Adaptive Gaussian Mixture Model, therefore the final output of the proposed algorithm is given by an *"And Operation"* between AP_n and MP_n. To clearly identify each object in the scene, the "and image" is further filtered using a morphological filter combined with size filtering operations. In particular we have adopted operations of erosions followed by closing (10 times), dilations followed by opening (15 times) and median statistic filter (with a kernel size of 17x17) thus obtaining an output image such as the one shown in Figure 3(d).


Frame time t
(a)
Output Image Algorithm Moving Ave...
(b)
Foreground Adaptive Mixture Gaussian Model
(c)
Current Frame
3
4
(d)
Figure 3: (a) Grabbed Frame, detected foreground by the (b) Moving Average Detection Algorithm, (c) Adaptive Gaussian Mixture Model, (d) Final output of the detection algorithm.

Finally, the number of fish in a frame is now obtained by applying a connected component-labelling algorithm. Having detected the fish, it is now necessary to firstly implement a tracking algorithm to estimate the total number of individual fish in a video.

5 TRACKING SYSTEM

We use a combination of two algorithms for tracking: the first one is based on the matching of blob shape features and the second one based on the histogram matching. For the "shape feature algorithm", we use Fis_n^i to denote the i^th fish, detected in frame *n*. We then use a feature vector $Fv_n^i = \{C_{n,x}^i, C_{n,y}^i, V_{n,x}^i, V_{n,y}^i, A_n^i, \theta_n^i\}$ for representing the parameters of the i^th fish, where $(C_{n,x}^i, C_{n,y}^i)$ is the centroid of the fish Fis_n^i, $(V_{n,x}^i, V_{n,y}^i)$ the average motion vector of the fish Fis_n^i, A_n^i the area of the fish Fis_n^i and θ_n^i the orientation (in degrees) of the fish Fis_n^i.

The motion vector is defined as a field of object velocities at each point in space that defines the 3D motion of objects in a time varying scene. The orientation of a blob is defined as the angle composed by the principal axis of the object and the vertical axis. Fis_n^i is compared to the fish in frame *n+1*, and Fis_n^i is matched with Fis_{n+1}^j if the following matching rules are satisfied:

$$\left|A_n^i - A_{n+1}^j\right| < Th_1 \qquad \left|\theta_n^i - \theta_{n+1}^j\right| < Th_2$$

$$\sqrt{\left(C_{n,x}^i - C_{n+1,x}^j\right)^2 + \left(C_{n,y}^i - C_{n+1,y}^j\right)^2} < Th_3 \tag{8}$$

Tracking by "colour matching" has been carried out by applying the Continuously Adaptive Mean Shift Algorithm (CamShift), which is an adaptation of the Mean Shift algorithm (Fugunaka, 1990).

Given a probability density image, Camshift finds the mean (mode) of the distribution by iterating in the direction of maximum increase in probability density (Intel Corporation, 2001).

The Probability Distribution Function (PDF) of images adopted in our work is the Histogram Back-Projection, which associates the pixel values in the image with the value of the corresponding histogram bin. The back-projection of the target histogram with any consecutive frame generates a probability image where the value of each pixel characterizes the probability that the input pixel belongs to the histogram of the target object. Hence, to generate the PDF, an initial histogram of the hue channel in HSV colour space is computed from the initial ROI of the filtered image. Tracks that are less than 3 frames long are ignored.

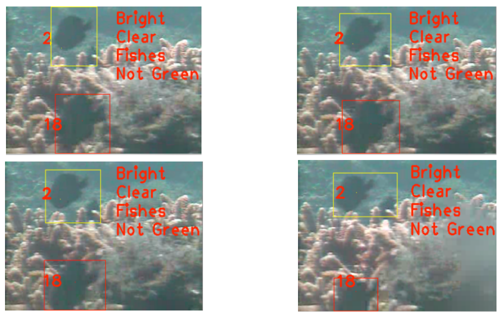


Figure 3: Tracking example with four frames grabbed at four consecutively times

Figure 3 shows example outputs of the tracking system, where the tracking is illustrated by colouring the bounding boxes of the detected fish using different colours (yellow for the one in the upper left and red for the lower left).

6 EXPERIMENTAL RESULTS

To evaluate the effectiveness of the proposed system, we tested our method on 20 different underwater sequences. These video sequences are sampled to 320×240 with a 24-bit RGB and at a frame rate of 5fps. Each video is about 1 minute long (300 frames).

The aim of this experiment is to determine the accuracy of its fish detection and counting abilities that make use of the fish tracking modules.

Our system can fail to extract objects of interest, thus miss out potentially interesting entities. This is called *False Negative (FN)*. Moreover, it can extract targets apparently of interest, but in fact, is a false identification, e.g. by considering a part of background as foreground. This error is referred to as *False Positive (FP)*.

We show our experimental results at two different stages: Fish Detection and Fish Counting.

Table 2 shows the detection results. The *Detection Success Rate (DSR)* is defined below:

$$DSR = 100 \cdot \frac{(ND - FP)}{NR} \qquad (9)$$

For each video, NR denotes the real number of fish in each frame; ND represents the total number of fish detected using our algorithm; FP and FN, respectively, store the values of False Positives and False Negatives. The performance of the detection algorithm is promising: up to 89.5% and no less than 80% of fish have been correctly detected. The number of False Positives has occurred due to the un-controlled open water environment with moving background objects and videos being shot in murky waters. This error is largely corrected when the Fish Tracking algorithm is carried out.

Table 2: Detection Algorithm Results

Video	NR	ND	FP	FN	DSR
1	160	146	7	21	86.8%
2	94	80	4	10	80.5%
3	212	198	9	23	89.5%
4	83	74	3	12	85.5%
5	76	65	2	13	81.5%

The Fish Tracking algorithm has shown excellent results with about 90% accuracy. The 10% of error was caused by the absence of a sophisticated fish identification algorithm that would help distinguish e.g. cases like where two fish pass in front of each other.

Based on the two previous algorithms, additional fish counting algorithm is carried out to count the total number of individual fish in a video. The overall results for fish counting are given in Table 3. The *Counting Success Rate (CSR)* is formulated below:

$$CSR = 100 \cdot \frac{(FC - OC)}{NF} \qquad (10)$$

NF is the total number of individual fish in the entire video. FC is the number of fish counted by the algorithm. OC is the number of fish overcounted, due to the failure to detect the same fish in intermediate frames in the detection algorithm. This leads the same fish to be tracked several times and thus overcounted. ND is the number of fish not detected.

Table 3: Fish Counting Results

Video	NF	FC	OC	ND	CSR
1	30	28	1	3	90.0%
2	12	10	0	2	83.3 %
3	54	54	4	4	92.5%
4	12	14	4	2	83.3%
5	12	13	4	3	75.0%

Considering the large amount and different types of noise that affect these videos, the above findings of an average success rate of 85.72% over all 20 movies (about 8000 frames) is more than satisfying. Often the overcounting errors are caused by the low frame rate presented in the video (fish move too fast to be successfully tracked) and the low quality of the images.

The obtained results are considered excellent when compared with other similar algorithms where fish counting was carried out in a constrained environment. For instance, (Morais Erikson et al, 2005) reported a 81% success rate on fish counting in a constrained environment, i.e. in a fish tank with fixed number of fish and in a controlled lab. (Petrell et. al.,1997) and (Ruff et. al. 1995) proposed video-based systems to measure fish number and average fish size with images taken in bordered cages.

The algorithm, implemented in C++ with Intel OpenCV 1.0 library, takes about on average 85 seconds for processing a video of 60 seconds on a Intel Core 2 Duo 2.0GHz with a 1GB Ram. The same system operates close to real time performance using an Intel Core 2 Duo Extreme 2.8GHz.

7 CONCLUSIONS AND FUTURE WORK

This paper presented a machine vision system that automatically determines and annotates characteristics of underwater video images. The main goal of our system is to provide marine biologists with useful analysis therefore allowing them to cut down viewing and searching time of raw videos. Examples of analysis done are the identification of environmental conditions (e.g. the brightness or smoothness of a video), the numbers of fish present in a frame (therefore helping locate useful frames in a video), the total number of fish in a video (help selecting between videos) and the overall quality of a video (helping select videos based on desirable qualities). We note that the observed accuracy of 85% may be considered as a satisfactory estimate, since it provides a reasonable approximation of the actual fish flow, the varying environmental conditions in an open unconstrained space and the changeable status of the sensors used.

Unlike other existing fish image processing methods which are mostly conducted in a lab, our approach provides a reliable method where analysis are carried out on data captured in their natural habitat where conditions may vary drastically which inevitable introduced uncontrollable interferences, e.g. murky water, algae on camera lens, moving plants and unknown objects, low contrast, low frame rates, etc.

Further development for fish classification and occlusion handling is in progress. Fish classification for the EcoGrid videos is a very challenging task due to the low quality images and varying scenarios that need to be taken into account.

New algorithms for detection and tracking will be implemented in order to investigate improved efficiency. Furthermore, the algorithms developed to perform the video analysis, (such as pre-processing, detection, tracking and counting) could be integrated into a more generic architecture so that the *best* algorithm for each step will be selected. The performance level for the algorithms will be determined by a measure such as processing time or certain user provided requirements. Thus a combination of optimal algorithms to perform the video analysis could be utilized.

REFERENCES

Brehmera, P., Do Chib, T., Mouillotb D., (2006) Amphidromous fish school migration revealed by combining fixed sonar monitoring (horizontal beaming) with fishing data. *Journal of Experimental Marine Biology and Ecology. Vol. 334, Issue 1, pp. 139-150.*

Petrell, R. J, Shi X, Ward R. K., Naiberg, A. and Savage C. R. (1997) Determining fish size and swimming speed in cages and tanks using simple video techniques, *Aquacultural Engineering, Vol.16, pp. 63-84.*

Faro A., Giordano D., Spampinato C. (2004). Soft-Computing Agents Processing Web Cam Images To Optimize Metropolitan Traffic Systems, *LNCS, Book CVG, Netherlands, Vol. 32, pp. 968-974.*

Fugunaga, K. (1990): *Introduction to Statistical Pattern Recognition*, 2nd Edition, Academic Press, NY, 1990.

Intel Corporation (2001): *Open Source Computer Vision* Library Reference Manual.

Morais Erikson F., Campos Mario F. M., Pádua Flávio L. C. and Carceroni Rodrigo L. (2005) "Particle Filter-based Predictive Tracking for Robust Fish Counting", *2005 SIBGRAPI, pp: 367 - 374*

Otsu N. (1979) "A Threshold Selection Method from Gray-Level Histograms", *IEEE Transactions on SMC, vol. 9, pp. 62-66.*

Rajagopalan N., Burlina P., Chellappa P. (1999) "Higher Order Statistical Learning for Vehicle Detection in Images", *Proceedings of ICCV99, 20-25 September, Corfu, Greece.*

Ruff, B. P., Marchant J. A., and Frost A. R. (1995) "Fish sizing and monitoring using a stereo image analysis syste applied to fish farming". *Aquacultural Engineering, Vol. 14, pp.155-173.*

Rouse W. (2007). Marine Biology Research Experiment: Population Dynamics of Barnacles in the Intertidal Zone. *May 27, 2007.*

Schlieper, C. (1972). *Research methods in marine biology.* University of Washington Press, Seattle, 1972.

Zivkovic Z. (2004) Improved adaptive Gausian mixture model for background subtraction, *Proceedings of ICPR 2004, August 23-26, Cambridge, UK.*