Journal of Experimental Marine Biology and Ecology 452 (2014) 105–110

Contents lists available at ScienceDirect

Journal of Experimental Marine Biology and Ecology

journal homepage: www.elsevier.com/locate/jembe

Automated marine turtle photograph identification using artificial neural networks, with application to green turtles

Steven J.B. Carter [a,*], Ian P. Bell [b], Jessica J. Miller [c], Peter P. Gash [d]

[a] University of Tasmania, Private Bag 37, Hobart, Tas 7001, Australia
[b] Queensland Department of Environment and Heritage Protection, Townsville, Qld 4810, Australia
[c] Flinders University, G.P.O. Box 2100, Adelaide, SA 5001, Australia
[d] Lady Elliot Island Eco-Resort, P.O. Box 348, Runaway Bay, Qld 4216, Australia

ARTICLE INFO

Article history:
Received 2 July 2013
Received in revised form 12 December 2013
Accepted 14 December 2013
Available online 11 January 2014

Keywords:
Artificial neural networks
Automated photo identification
Bio-monitoring
Marine turtle populations

ABSTRACT

Marine turtle population studies to date have relied on flipper tags or other physical markers to identify individuals previously caught and released. This approach is not entirely successful, motivating us to develop a method for producing an automated turtle photograph identification (photo ID) system. This advancement uses artificial neural networks to compare a digital photo of an individual turtle with a database of turtle photos. Unlike many animals, marine turtles have distinctive facial characteristics, making them ideal candidates for automated photo ID systems. It is easy to gather the large number of good photos of tagged turtles needed to train and test the system; the pattern of interest can be distinguished in a relatively small number of pixels; and it is possible to take suitable photos of both nesting and free swimming turtles. We have used this method to develop a photo ID system, MYDAS, for green turtles (*Chelonia mydas*), with individual animals identified by their distinctive post-ocular scute patterns. MYDAS has a success rate better than 95% in correctly determining whether a new photo matches a photo in a database, and is now being applied to the green turtle population of Lady Elliot Island in the southern Great Barrier Reef.

1. Introduction

Most marine turtle population surveys rely on the application of metal or plastic flipper tags to identify individual animals caught and released in previous surveys. But flipper tags rarely last longer than 20 years, and tag loss can occur within months if the tag is not properly applied, while a turtle can live for decades after its first capture. A flipper tag can cause necrosis if it compresses tissue to the point of blocking vascular circulation, and flipper necrosis may also occur if tags are crushed by turtles nipping each other, or nipping their own tags (Balazs, 1982). To date, implanting a Passive Induced Transponder (PIT) tag is the leading alternative to a flipper tag (Gibbons and Andrews, 2004; Limpus, 2008), however PIT tag costs may be high (~A$10), with typically 100s to 1000s of PIT tags needed each year to monitor a single turtle stock.

These issues motivated us to develop a method for producing an automated marine turtle photo identification (photo ID) software system, training a set of artificial neural networks (ANNs) to compare photos of turtles, with individual animals distinguished by their distinctive facial characteristics. Our interest in determining annual survivorship and population trends via a capture–mark–recapture model means our photo ID systems compare photos of individuals of the same species (some photo ID systems aim to identify the species in the photo). We chose to produce a photo ID system for green turtles, *Chelonia mydas*, first, since it was easy for us to obtain the large number of photos required to train and test the neural networks, and because green turtles have very distinctive post-ocular scutes, facilitating work to refine methodology details. This green turtle photo ID system "MYDAS" can be obtained by contacting either of the two lead authors (Carter and Bell).

We start by discussing the barriers that prevent development of automated photo ID systems for population studies of many animal species, and why marine turtles are ideal candidates for such systems. We describe the image processing steps to isolate the pattern of interest in a photo, in the case of green turtles post-ocular scutes (Fig. 1); the neural network architecture and training procedure; and how pairs of photos are compared. We discuss the performance of MYDAS, and discuss ways a photo ID system can be improved as technology allows, and as more photos become available.

Finally, we outline current work to apply MYDAS to the green turtle population of Lady Elliot Island on the Great Barrier Reef. MYDAS will support ongoing monitoring of the island's green turtle population using flipper tags, by identifying nesting turtles that have lost their tags. The system will also be applied to photos of turtles in open water, including identification of sub-adults, males and non-breeding female turtles.

* Corresponding author. Tel.: +61 3 6231 0500.
E-mail address: steven.carter@utas.edu.au (S.J.B. Carter).

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http://dx.doi.org/10.1016/j.jembe.2013.12.010

Fig. 1. Typical photograph of the left side of a green turtle's head.

2. Barriers to automating animal photo ID systems

Photographic identification of individual animals, based on distinctive individual morphological characteristics, is a non-intrusive way to obtain information on their behaviour, population size, survivorship, and life history. Applications to date include seals (McConkey, 1999); cheetahs (Kelly, 2001); zebra (Peterson, 1972); giraffes (Foster, 1966); elephants (Douglas-Hamilton, 1973, Goswami et al., 2007); lions (Schaller, 1972); cetaceans (Hammond et al., 1990); sharks (Van Tiehoven et al., 2007); crustaceans (Frisch and Hobbs, 2007); and manta rays (Couturier et al., 2011). There is also clear potential to apply photo ID methods to at least some marine turtle species, including leatherback turtles (Dutton et al., 2005); loggerhead turtles (Schofield et al., 2008); and green turtles (this paper).

Automating an animal photo ID system has many applications, especially when a photo must be compared to a database of hundreds of photos. ANNs are routinely used to automate such pattern recognition tasks, but MYDAS is the first such automated photo ID method for marine turtles, and we are not aware of any similar system applied to other animals.

The main barriers to producing an automated animal photo ID system derive from the need to train and test the ANN. To understand the issues, consider a post code recognition system (Dreyfus, 2005; LeCun et al., 1989). The image of a post code box on a letter typically contains 100 pixels; a pixel value can be coded 1 or 0 depending on whether or not the post code character touches the pixel; and it is easy to produce, however many images are required to train and test the neural network. The task of comparing animal photos is far harder. The first barrier is the availability of good software and computing power, since the pattern of interest may require thousands of pixels to be adequately resolved, and binary pixel values are not sufficient if colour is important. The march of technology is helping to remove this barrier. Excellent ANN and image processing software is now available; and desk-top computing power is sufficient to apply such software to images containing large numbers of pixels. Also, digital cameras and laptop computers are standard field survey tools, so a photo can quickly be compared to a database of photos.

The next barrier to automating an animal photo ID method is the need to have a sufficient number of photos to train and test the artificial neural network. The first step is to develop an ANN architecture and training strategy for good photos, free of problems such as tilt or shadows. Once an ANN has been trained in this fashion, it can be further trained until it is able to recognise the pattern of interest in photos of lesser quality. This is a standard approach: an ANN to recognise hand written post codes is first trained to recognise typed numbers.

High quality photos of marine turtles captured during a survey can all be taken from about the same angle and distance, and taking a similar photo of a turtle underwater is often possible, especially if the turtle is resting. We used green turtle photos taken during nesting turtle surveys on the Great Barrier Reef. Photos of previously tagged turtles provide certainty in the training exercise, with no doubt whether the ANN is correctly comparing two turtle photos, and such surveys can also produce the necessary number of photos needed for training the network. Another reason for choosing green turtles for the first automated photo ID system is that their post-ocular scute patterns are highly polymorphic and unique to individuals, but simple enough to be represented by a reasonably small number of pixels, which facilitated our work to optimise the ANN architecture and training strategy.

For many animals, obtaining enough good photos for the initial training exercise is difficult, and photos of animals in the wild are influenced by many effects (e.g. blur, tilt, glare, shadows, perspective, and poor visibility), preventing development of automated photo ID systems even when individual animals have clear distinguishing features. In the future, image processing methods may reduce the effort needed by an ANN, but at present it is not trivial to automate such methods, and progress is slow even though computer vision is an area of intense research effort (e.g. Meer, 2012).

The final barrier to automating an animal photo ID method is the need to apply it to a meaningful number of individuals. Fortunately, genetic and mark–recapture studies of marine turtles (FitzSimmons et al., 1997) have concluded that turtles demonstrate high levels of site fidelity by returning to breed at their natal rookeries. Similarly, at the completion of breeding, both male and female turtles display strong fidelity to their feeding areas (Seminoff et al., 2003). The implication is that a separate database of photos can be maintained for each nesting and feeding area, thus reducing the risk of confusing two turtles with similar distinguishing scute patterns.

3. Image acquisition and pre-processing

Our marine turtle photo ID system (MYDAS) uses the post-ocular scutes on the left side of a green turtle's head to identify the animal. The software is written in Matlab, using its image processing and ANN toolboxes. Fig. 1 shows an acceptable photo: the camera is held level with the turtle's head, which has been cleaned of sand, and the photo includes a card showing the turtle's flipper tag number. A 2 MB photo is sufficient to adequately resolve the post-ocular scutes.

MYDAS can be used as soon as the photo is made available to the computer, making it suitable for field applications. As shown in Fig. 2, MYDAS prompts the user to window out the post-ocular scutes, identify the scute points above and below the turtle's eye, and define the scute outline. MYDAS then produces the image in part C of Fig. 2, which has about 1 million pixels (~800 rows $\times$ ~440 columns $\times$ 3 colours), and is the portion of the original photo relevant to the pattern recognition exercise. This image is saved in the database, and is the starting point for the photo comparison exercise.

MYDAS follows an automated algorithm to prepare a scute image for input to an ANN. First, histogram intensity equalisation is applied to the red, green and blue components of the pixels. Then the image is converted to grayscale intensity, with pixel values ranging from 0 to 255, and resized to reduce the number of pixels while still adequately resolving the pattern of interest. For green turtles, we found that an image of 53 rows $\times$ 29 columns (about a factor of 15 reduction) is sufficient to resolve the post-ocular scute pattern. The image is then inverted, so that white pixels (value = 255) that are not part of the scutes become black (value = 0), which facilitates training the ANN. This 2-D array of numbers is then converted to a 1-D array of $53 \times 29 = 1537$ numbers.

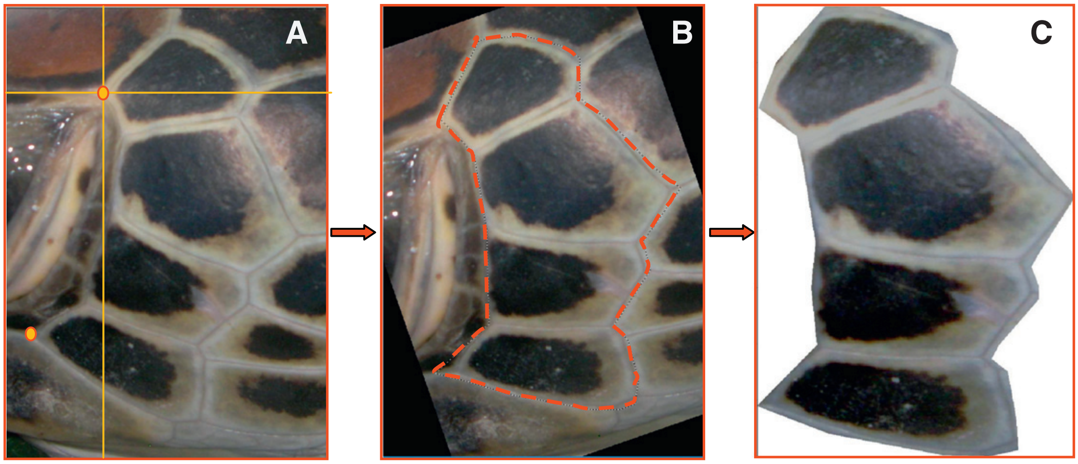

Fig. 2. MYDAS facilitates isolating the portion of the (colour) photo containing the post-ocular scutes. The cross-hair cursor is used to identify the scute points above and below the turtle's eye (the white dots). MYDAS rotates the image to vertically align these points to standardise the image's orientation, and the result is image B. The User then defines the polygon that outlines the scutes (the dotted line in image B), and MYDAS uses this to isolate the scutes (image C).

4. Artificial neural network architecture

Beale et al. (2012), and Hagan et al. (1996), provide introductions to ANN theory. A three layer feed-forward ANN was appropriate for an animal photo ID system, consisting of an input layer of neurons, a hidden layer of neurons, and a single output layer neuron. Each neuron in the input layer accepts a set of inputs (x_i), applies a weight (w_i) to each input, sums the weighted inputs, adds a bias (b), and its transfer function, f, then produces an output $y = f(\Sigma w_i x_i + b)$. Similarly, each neuron in the hidden layer accepts the outputs of all the input layer neurons, and produces its own output, which is directed to the output layer neuron.

MYDAS uses 55 input layer neurons and 8 hidden layer neurons, which trial and error found to be approximately the simplest architecture able to identify the post-ocular scute pattern in the input data. To help avoid the risk of overfitting, it is good practice not to use a network larger than is necessary. We chose tangent-sigmoid transfer functions for both the input and hidden layer neurons. The S-shaped part of this transfer function lies between about -3 to $+3$, producing an output between -1 and $+1$. Input values lower than about -3, or higher than $+3$, produce constant responses of -1 and $+1$ respectively.

A single output layer neuron accepts inputs from all the hidden layer neurons, and produces the final output of the ANN. We used a linear transfer function for this neuron, and trained the ANN to produce an output of 1 if the input represents two photos of the same turtle; and an output of 0 if the input represents two photos of different turtles. The use of a linear transfer function means that the output value is not constrained to be either 1 or 0, and its proximity to one or other of these values is a measure of the confidence of the ANN in its prediction.

5. Artificial neural network training

Pre-scaling input data can facilitate training of the ANN. In the case of MYDAS, the ANN input is a set of 3074 numbers (2 photos $\times$ 1537 pixels per photo) which range from 0 to 255, so dividing them by 1000 assists the training algorithm to adjust the weights and bias until the weighted sum of the inputs to a given neuron lies in the transfer function's effective range of -3 to $+3$.

Two turtle survey campaigns produced photos of 72 turtles to train and test MYDAS. Each turtle was photographed twice, 36 turtles were photographed a third time, and all the photos were pre-processed to isolate the post-ocular scutes. MYDAS prepared a training data set by reading in the two sets of 72 scute images, and producing 72 sets of 3074 numbers, each representing a pair of photos of the same turtle, and associated with a target output value of 1 (i.e., a photo match). Each scute image was also twice paired randomly with a scute image for a different turtle, giving 144 sets of 3074 numbers, each representing a pair of photos of different turtles, and associated with a target output value of 0 (no match). Adding additional pairs of scute images from different turtles would risk the training algorithm producing an ANN biassed towards predicting an output of 0 (no match). However, it is common practice to produce additional pairs of images by reversing the order of the two images in each pair, and doing this resulted in $2 \times (72 + 144) = 432$ pairs of images in the training data set.

MYDAS prepared a check data set in a similar fashion, using the set of 36 photos, and one of the sets of 72 photos. Each of the 36 scute images was paired with a different scute image from the same turtle, and was also paired with a scute image from a different turtle. Additional check data were produced by reversing the order of the two images in each pair, giving $2 \times (36 + 36) = 144$ sets of 3074 numbers in the check data set.

The MYDAS ANN was trained using the Matlab backpropagation algorithm *trainlm*, which compares the ANN's prediction to the required output value (0 or 1), and adjusts the neuron weights and biases using gradient descent, momentum and an adaptive learning rate, working backwards from the output layer to the input layer (Hagan and Menhaj, 1994). Batch mode learning is used, whereby the algorithm considers the ANN's predictions for all the training data set image pairs, instead of proceeding pair by pair.

The ANN training is stopped when the mean squared error (MSE) of the residuals has reduced to 0.2, which usually takes about 100 training epochs. An epoch refers to the cycle of making predictions, examining the residuals, and adjusting the neuron weights and biases, and the training algorithm parameters. A smaller target MSE risks producing an ANN that overfits the training data set, and is not able to generalise. The trained ANN is then applied to the check data set. Predictions greater than 0.5 are interpreted as a determination that the pair of photos are of the same turtle, and predictions less than 0.5 are interpreted as a determination that the pair of photos are of different turtles. The ANN is accepted if it makes correct predictions for at least 80% of the check data.

ANN predictions between about 0.4 and 0.6 are interpreted as the ANN being uncertain in its prediction. Given this, if a photo ID system uses only one ANN to compare photos, then in the case of MYDAS it would perform at about the 80–85% level. Better performance can be achieved by training many ANNs, and applying all of them to the prediction task. For each training exercise, a new ANN is established, with a

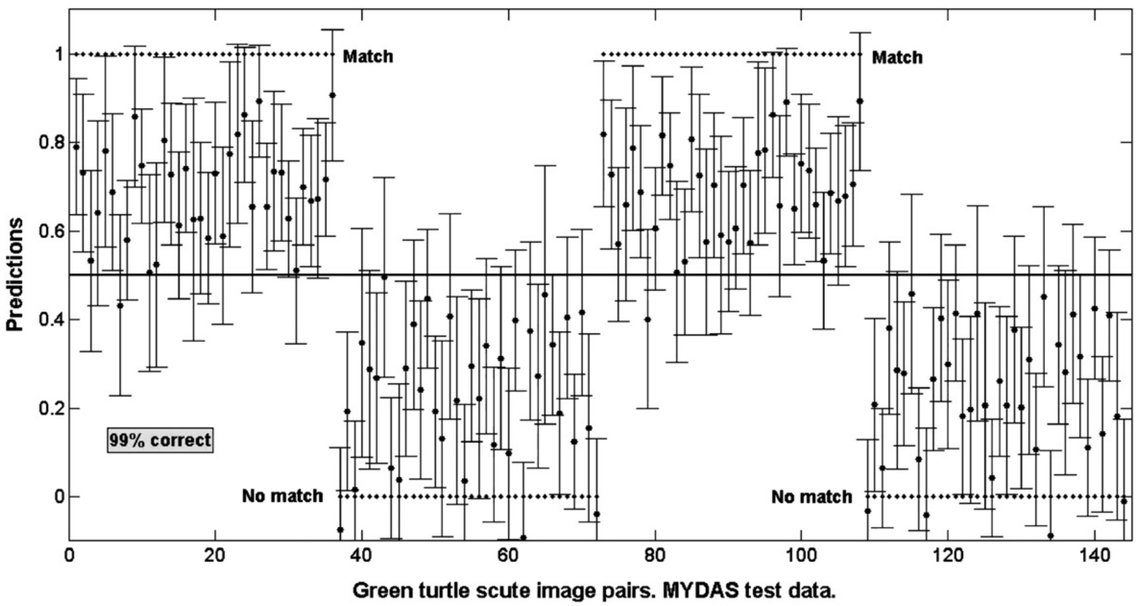

Fig. 3. MYDAS typically makes correct predictions for more than 95% of check scute image pairs (36 matches, 36 no-matches, and reversal of the order of the images).

new set of initial neuron weights and biases. The training and check data sets are also different, because the pairs of photos for different turtles are randomly selected. MYDAS automatically produces a total of 50 ANNs, and the comparison of a pair of scute images is thus the mean of 50 predictions, with the error bar being the standard deviation of the 50 predictions.

6. MYDAS performance and system improvements

Fig. 3 shows the result of applying MYDAS to a check data set. The random nature of pairing scute images from different turtles means that each check data set is unique, and MYDAS typically achieves correct predictions for more than 95% of the image pairs. Importantly, the error bars for most of the predictions in Fig. 3 lie entirely on the correct side of the 0.5 line that separates the match and no-match determinations.

Fig. 4 shows the result of MYDAS searching the database of turtle photos, seeking a match for a new photo, in this case a photo of the first turtle (K03982) in the database. Four turtle photos in the database are predicted by MYDAS to be matches to the new photo (i.e. the predictions are greater than 0.5), and the best match is correctly determined to be turtle K03982.

The performance of an automated turtle photo ID system can be improved as more photos become available, by further training (not retraining) of the ANNs using training data sets that include image pairs in the previous check data set that resulted in either incorrect predictions, or predictions between about 0.4 to 0.6, indicating that the system was not confident of the prediction. Also, the algorithm that produces the inputs to the photo ID system can be refined without reprocessing the photos in the database. For example, it might be extended to include noise removal or deblurring routines, or it might

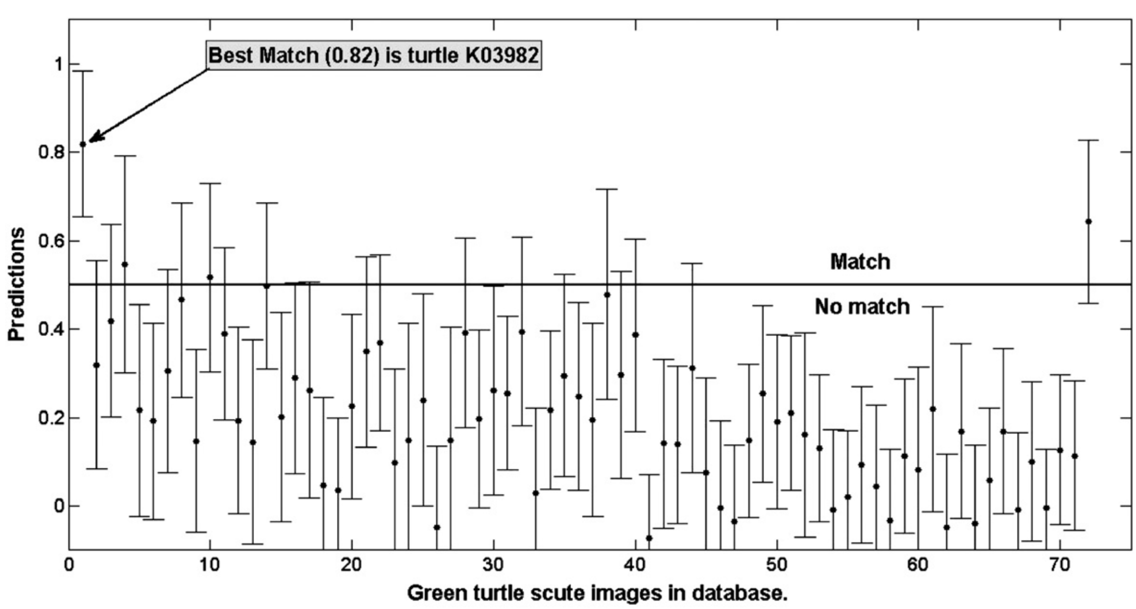

Fig. 4. Example of MYDAS correctly matching a new scute image with the scute image for the first turtle (K03982) in the database.

be deemed appropriate to resize the image by a smaller factor, to better resolve the pattern of interest (which would in turn require greater computing power to be available to enable the use of larger ANNs).

The ANN training procedure can also be improved once a sufficient number of scute images are available to prepare two check data sets. At present, the ANN training proceeds until the MSE of residuals has decreased to the goal of 0.2. A better approach is to monitor the MSE of residuals for a first check data set, which will initially decrease with each training epoch, and then start to rise when the ANN starts to overfit the pattern, at which point the training process is stopped. The true performance of the ANN is then confirmed by applying it to the second check data set.

Finally, MYDAS compares two photos by using the mean of 50 ANN predictions, with each ANN correctly processing at least 80% of a check data set. The improvements outlined above may enable the 80% acceptance threshold to be raised.

7. Application to Lady Elliot Island

In October 2013, we started to apply our first turtle photo ID system, MYDAS, to Lady Elliot Island (LEI), in the southern Great Barrier Reef, in a collaborative project between the Queensland Department of Environment and Heritage Protection, and the LEI eco-resort. LEI has a discrete long-term feeding and nesting population of several hundred green, loggerhead, and hawkbill turtles, an ideal site for an automated turtle photo ID system. The use of flipper tags to monitor LEI's turtle population will continue, with MYDAS supporting and extending this traditional monitoring approach.

MYDAS is being applied to photos of nesting green turtles, and also to open water photos of turtles, taken by divers and snorkellers, which will extend our understanding of LEI's sub-adult, male and non-nesting female turtle populations. Only photos of turtles with flipper tags will be used to further train MYDAS, to ensure the probity of the training data set. Photos are labelled LEI_C1_C2_C3_C4_C5, where C1 to C5 are codes respectively for the date; location on the island (North, East, etc.); beach or water; turtle's head or entire turtle; and the tag number, if the turtle has a tag. An Excel spreadsheet is used to record the photos taken of each turtle, and ancillary information such as whether the turtle had any injuries.

The performance of MYDAS when applied to turtle photos taken years apart will be studied, since scute patterns may change, fade, or be affected by marine growth as the turtle ages. However, if a human observer is able to correctly compare turtle photos taken years apart, then it should be possible to train an ANN to do likewise.

8. Conclusions

Our motivation for developing an automated marine turtle photo ID method was to support conventional turtle survey programmes, which usually use flipper tags to identify individual animals. A turtle is likely to outlive a flipper tag by decades, and a photo ID system can be used in the field to identify a turtle that has lost its tag. The photo ID system can also be applied to turtles in the open water, including juvenile and male turtles, since it is easy to take suitable photos of turtles in the open water. Automation is achieved using an ordinary pattern recognition exercise, in which ANNs compare the pattern of interest in two photos, and conventional turtle surveys can provide the large numbers of tagged turtle photos that are needed to bring certainty to the process of training and testing the ANNs. We have described how to develop an automated marine turtle photo ID system, as illustrated by our green turtle photo ID system, MYDAS. Green turtles have distinctive post-ocular scutes, so the required photo is of the side of a turtle's head, and the scute pattern can be adequately defined by a small number of pixels, which facilitated our work.

Our photo ID system has three aspects of interest to artificial intelligence specialists. First, it uses 50 separate ANNs to compare the scute patterns in two photos, so the outcome of the comparison is the mean of 50 separate predictions. Second, the ANNs have a single output layer neuron with a linear transfer function, allowing us to assess the confidence of a given image match or no-match determination. Third, improvements to the system can be made without having to re-do the initial work to isolate the pattern of interest in the original turtle photo, and we have discussed the expected nature of these improvements.

MYDAS has a success rate better than 95% in correctly determining whether a new photo matches a photo in a database. One research goal is to understand the extent to which scute patterns change or fade as a turtle ages, and we anticipate that the photo ID system will need to be further trained, as photos become available, to tolerate such things. We are planning to develop a second photo ID system for application to loggerhead turtles.

Acknowledgements

We thank the Queensland Department of Environment and Heritage Protection (DEHP) for supporting the field work component of this project to obtain turtle photographs. We also thank Peter Gash's team on Lady Elliot Island for helping to apply MYDAS to the island's turtle population, and assisting the ongoing monitoring work being carried out by DEHP's Mon Repos turtle rookery research station, led by Colin Limpus and John Meech. [**ST**]

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