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Feature Extraction of the Carapace for marine Turtle Species Categorization

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Abstract: To date, photograph identification systems for individual marine turtles are focused on the facial profile, and scute patterns on the top of the head, and neck. However, to the best of knowledge, there seems to be no photograph identification system focused on recognising marine turtle species based on characteristics of the carapace. Studies argued that by including more features, such as characteristics of the shell, the systems could enhance its classification accuracy. However, previous works have failed to address why none of them used characteristics of the shell for identifying marine turtle species. In this research, a comprehensive study of the effectiveness of the features extracted, colour, shape, and texture, from the carapace is conducted. Several experiments are carried out using the data extracted to find out the suitable data dimensionality, and the "best" hyper-parameters to train the neural networks. The expectation of this research is that these features can be used to develop a non-intrusive automated system for pattern recognition of marine turtle species using the characteristics of the carapace.

Keywords: Gray level co-occurrence matrix, HSV, RGB, Seven Invariant Moment, Neural Network.

I. Introduction

Studies in marine biology and ecology have proved that photograph identification is a reliable system for collecting and identifying information about animals' life story, behaviour, population, and survivorship (Carter et al. 2013; Foster, 1966; McConkey, 1999). Usually, these systems are built based on distinctive morphological characteristics of the animals. Previous studies have proved that morphological characteristics are robust features to classify individual animals (Carter et al., 2013; Valdés et al., 2014; Van Tiehoven et al., 2007). Nowadays, photograph identification systems are used to protect endangered species, such as sea turtles, because their population declined dramatically due to human behaviour and climate change (Dutton et al., 2005). Researchers in the field of conservation of marine turtles have been struggling to extract the unique features for identifying an individual animal (Carter et al., 2013; Ekambaram et al., 1973; Jean et al., 2010; Lloyd et al., 2012; Pauwels et al., 2008; Schofield et al., 2008; Valdés et al., 2014). Remarkable was the conclusion made by Valdés et al., (2014) that none of the photograph identification systems is error-free. However, Lloyd et al. (2012) and Valdés et al. (2014) argued that to develop a robust photo identification system more features should be extracted from the marine turtles. Then these elements should be integrated into the current systems to improve their classification accuracy. The previous study made by Lloyd et al. (2012) suggested that, by including features such as characteristics of the shell, not only can all turtles be uniquely identified, but also the success rate of the classification techniques may be improved. To the best of knowledge, there seems to be no photograph identification system focused on recognising marine turtle species using characteristics of the carapace. Therefore, extracting proper features is crucial for the satisfactory design of any pattern classifier (Tan, 2004). Features for segmentation of images such as the colour, Seven Invariant Moment for shape, and Gray level co-occurrence matrix (GLCM) for texture have been proving that they are reliable in solving the classification problems (Alli et al., 2013; Bora et al., 2015; Almeida et al., 2015; Golpour et al., 2014). Savakar (2012) used colour and texture to identify bulk fruits and concluded that texture had performed better than colour. In contrast with Mallick et al. (2013) that used colour and texture for identifying and classifying similar looking food grains, they concluded that the colour outperformed texture. Seven Invariant Moments for shape and Gray level co-occurrence matrix for texture description have been extensively used for classification problems in many fields of research, for example, in animal footprint, and segmentation of historical documents images (Alli et al., 2013; Mehri et al., 2013). However, these studies highlighted that the combination of features had performed much better in the prediction process (Mallick et al., 2013). Usually, neural network (NN) is used to build the models using these features (Mallick et al., 2013; Savakar, 2012). NN has been shown to be a powerful pattern recognition paradigm in a variety of real-world classification tasks such as in industry, business, science, and medicine (Carter et al., 2013; Yadav et al., 2014). However, the raw data created by the features and their combination can decrease the precision of the networks. Researchers use pre-processing filters to perform some work on the raw data to reduce the factors that could affect the training of the models negatively. Moreover, pre-processing can be seen as a technique used to improve the accuracy of classification (Zaamout et al. 2012).

The aim of the present work is to perform a comprehensive investigation on the effectiveness of the features extracted from the carapace to recognise marine turtle species. The raw data passes on to pre-processing and then it is classified using the neural network.

II. Material and Methodology

For feature extraction, and image pre-processing a script written in MATLAB 2013a is used. Weka 3.7 is used to pre-process the raw data, train, and test the neural networks (Hall et al., 2009).

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A. Image acquisition

The photographs were collected from flickr.com, Fuze Ecoteer Perhentian Turtle Project database, and Turtle Island Restoration Project database. Different types of photographs were collected such as marine turtle in open water, resting, and nesting. 159 pictures of marine turtle species were provided, 87, 46, and 26 for Green Turtle, Leatherback, and Olive Ridley, respectively. Due to the non-standardization of the images' size, some pre-processing was needed to create a fair training process of the model.

B. Feature extraction

The techniques used in this research are selected because they are robust in collecting information independent of the scale, orientation, rotation, and translation. Also, they have proved to be related to the way the human visual system identifies an object. The region of interest (ROI) is utilised to choose the area of the image which contains the carapace. This process reduces the factors that could affect the extraction of characteristics of the carapace (Krijger et al., 2008). The process of selection of the ROI is unique to each image, and it was done manually using a rectangular form in required area (Figure 1).

Figure *1*: ROI facilitated isolating the portion of the photo containing the carapace.

In this research, due to the small training set and the non-standardization of the pictures' size, the pictures are resized to four different dimensions 64, 128, 256, and 512 (Hashemi, 2012). The resize process was carried out using a technique to keep the pictures' aspect ratio (MathWorks, 2014c). For each image five samples are used, four samples are results from the resized image plus the original image. In total 810 patterns are used, 440, 240, and 130 for Green Turtle, Leatherback, and Olive Ridley, respectively. The data was randomly divided into two parts to guarantee that a right amount of instances were used to train and test the networks. 75% of images of each species were used to train the networks, and 25% of each species were used to test the networks.

1) Colour feature extraction

First, the original image was separated into different channels, red, green, and blue. Four statistical features were applied separately in each channel (Equation 1, to 4). Secondly, the original image was converted to HSV colour space. Similarly, the four statistic features were applied separately to the two channels called chrominance, Hue (S), and Saturation (S). Finally, in total twenty colour features were extracted from the carapace (Bora et al., 2015; Golpour et al., 2014).

$$Mean = \sum xx \sum y\, P(x,y) \quad (1)$$

$$Variance = \sum x,y\, P(x-\mu)^2 P(x,y) \quad (2)$$

$$Range = Max\big(P(x,y)\big) - Min\big(P(x,y)\big) \quad (3)$$

$$\sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i-\mu)^2} \quad (4)$$

2) Shape feature extraction

One of the most used techniques to describe shapes of objects in various environments is edges or corners. In this work, the Canny method was used to represent the edges of the carapace because Canny filter is used to detect robust and real weak edges. Moreover, it is less likely than the other methods to be fooled by noise (MathWorks, 2014a). Afterwards, Seven Invariant Moments are used to extract the characteristics of the carapace based on the edges following the Equations 4 to 11 (Alli et al., 2013).

$$m1 = n_{20} + n_{02} \quad (5)$$

$$m2 = (n_{20} - n_{02})^2 + 4n_{11}{}^2 \quad (6)$$

$$m3 = n_{30} - n_{12}{}^2 + 3n_{21} - n_{03}{}^2 \quad (7)$$

$$m4 = n_{30} + n_{12}{}^2 + 3n_{21} + n_{03}{}^2 \quad (8)$$

$$m5 = (n_{30} - 3n_{12})(n_{30} + n_{12})[(n_{30} + n_{12}{}^2) - 3(n_{30} + n_{12})^2] + (3n_{12} - n_{03})(n_{21} + n_{03})[3(n_{30} + n_{12})^2 - (n_{21} + n_{03})^2] \quad (9)$$

$$m6 = (n_{20} - n_{02})[(n_{30} + n_{12}{}^2) - (n_{21} + n_{03})^2] + 4n_{11}(n_{30} + n_{12})(n_{21} + n_{03}) \quad (10)$$

$$m7 = (3n_{21} - n_{03})(n_{30} + n_{12})[(n_{30} + n_{12})^2 - 3(n_{21} + n_{03})^2] + (3n_{12} - n_{30})(n_{21} + n_{03})[3(n_{30} + n_{12})^2 - (n_{21} + n_{03})^2] \quad (11)$$

3) Texture feature extraction

Gray Level Co-occurrence Matrix (GLCM) is adopted to obtain 16 texture features using contrast, correlation, energy, and homogeneity (Almeida et al., 2015; MathWorks, 2014b). Four orientations are used (0º, 45º, 90º, and 135º) with the distance between the pixel of interest and its neighbours equal to one (Equations 12 to 15).

$$Contrast = \sum_{i,j} |i-j|^2\, p(i,j) \quad (12)$$

$$Homogeneity = \sum_{i,j} \frac{p(i,j)}{1+|i-j|} \quad (13)$$

$$Correlation = \sum_{i,j} \frac{(i-\mu i)\,(j-\mu j)\,p(i,j)}{\sigma_i \sigma_j} \quad (14)$$

$$Energy = \sum_{i,j} p(i,j)^2 \quad (15)$$

C. Pre-processing of the raw data

The raw data is created using images of marine turtle species in different scales and scenarios that might happen in the real life application. In this work, various training sets are created based on the features extracted and their combinations. For each training set some pre-processing filters are applied to better prepare the data for the classification task. It is important to shuffle the order of the images or instances on the training set to create a stable system (Sengupta, 2009). Remove duplicates is another example of a primary filter used in the training sets to eliminate duplicate cases that can lead to false results in the evaluation and validation of the model. The normalisation filter is applied to normalise all attributes values on a particular range (Sola et al., 1997). In this research, due to the use of the sigmoid function, the data is normalised in the range [0, 1]. K-nearest neighbour was applied to remove outliers in the training sets (Rosin et al., 1995). Due to the small training sets k = 2 is used because it was proved that the higher the value of k the more instances are deleted. Due to the small training sets, a significant reduction of the classification accuracy can be observed. To overcome this issue, PCA was used to ensure a reliable estimation of the classification process reducing the number of features on each training set. The reason why attribute selection is important is that removing the variables with less variability across observations gives better predictive accuracy (Table 1).

Training sets	D_C	D_S	D_T	D_{C+S}	D_{C+T}	D_{S+T}	D_{C+S+T}
Number of features	20	7	16	27	36	23	43
Number of features (PCA)	7	2	3	9	9	5	11
Number of instances	608	507	486	607	602	539	602

Table 1: The properties of the datasets, where D# training set using any feature extracted.

D. Classification

The networks are created using feed-forward and trained using back-propagation (Negnevitsky, 2005; Nielsen, 2015). The number of features in Table 1 are the number of input layer neurons in each network. The number of hidden layer neurons is calculated automatically (Hall et al., 2009). The number of neurons in the output layer is equal to three because it represents the number of species used on the model to classify marine turtles, and the networks used the sigmoidal neurons in all the layers. The networks are validated using 10-fold cross validation method. Cross-validation method was used to achieve an unbiased estimate model performance and avoid overfitting in the training sets due to the small sample size (Krogh et al., 1995; Witten et al., 2011).

III. Results and Tables

Experiments are conducted to find out the suitable data dimensionality to ensure a reliable estimation of the classification. Table 2 shows the properties of the neural network trained using each dataset, where $NN_{\#}$ is a neural network constructed on any of the training set according to Table 1. Similarly, $NN_{\#\text{-}PCA}$ is a neural network built on any of the training set that applied the filter PCA according to Table 1. In general, the results in Table 2 revealed that the networks trained with the original training sets performed slightly better than networks built from the datasets that applied PCA. Unfortunately, the accuracy values decreased drastically when the networks were trained using $NN_{S\text{-}PCA}$, and $NN_{T\text{-}PCA}$; from NN_S 85% to $NN_{S\text{-}PCA}$ 79%; and from NN_T 86.6% to $NN_{T\text{-}PCA}$ 68.7%. In contrast with Asencio-Cortes et al., (2015) and Durairaj et al., (2015) that demonstrated that by applying PCA on the datasets the models' classification accuracy improved significantly. It could mean that the reason behind the poor performance using PCA was because of the small data samples. Also, due to low data dimensionality used to train both $NN_{S\text{-}PCA}$ and $NN_{T\text{-}PCA}$, the networks did not create a strong assumption about the data presented to the network. In contrast with Santamaria (2011) who argued that using lower feature dimensionality, fewer objects on the feature vector are required for training the model. However, whether this is true or not, it needs more investigation using more samples in the training sets.

Original datasets		PCA	
Networks	ACC (%)	Networks	ACC (%)
NN_C	98.85	$NN_{C\text{-}PCA}$	98.52
NN_S	85.40	$NN_{S\text{-}PCA}$	79.09
NN_T	86.63	$NN_{T\text{-}PCA}$	68.72
NN_{C+S}	98.52	$NN_{C+S\text{-}PCA}$	97.86
NN_{C+T}	99.00	$NN_{C+T\text{-}PCA}$	95.35
NN_{S+T}	87.20	$NN_{S+T\text{-}PCA}$	85.90
NN_{C+S+T}	98.34	$NN_{C+S+T\text{-}PCA}$	95.74

Table 2: Comparison between the neural networks trained by different datasets, where ACC means Accuracy.

Based on the results obtained from Table 2, each of the networks using original training sets were investigated to increase their performance. A trial-error-test process was conducted to determine the hyper-parameters of the networks that enhance their classification accuracy. Table 3 shows the properties of the neural network trained using each dataset, where $*NN_{\#}$ is a neural network constructed on any original training set which applied the trial-error-test. Remarkable were the results of the networks after applying the trial-error-test that improved their classification accuracy. Moreover, more epochs are needed when the small number of attributes are presented to train the network. $*NN_S$ used 1000 epochs, and $*NN_T$ required 900 epochs. These networks improved their classification accuracy from NN_S 85% to $*NN_S$ 86%; NN_T 86.6% to $*NN_T$ 88.9%. It can be inferred that, because the networks were trained using small data dimensionalities, more epochs were needed in the learning process for the neurons to get near the desired outputs.

Networks	Hyper-parameters				ACC (%)
	HL	Epochs	LR	M	
$*NN_C$	a	500	0.3	0.9	99.51
$*NN_S$	a	1000	0.3	0.2	86.19
$*NN_T$	a	900	0.3	0.2	88.89
$*NN_{C+S}$	a	500	0.8	0.2	99.18
$*NN_{C+T}$	a	500	0.9	0.2	99.34
$*NN_{S+T}$	a	500	0.7	0.2	91.47
$*NN_{C+S+T}$	a	500	0.7	0.2	99.00

Table 3: The properties of the best networks according to their hyper-parameters, where HL – Hidden Layers, LR – Learning rate, and M – Momentum, and ACC – Accuracy.

Table 4 illustrates the comparison results between the set of "best" networks (Table 3) and networks created using the original training sets (Table 2) to generalise in the new images (or test set). Colour proved to be a primary feature in recognising carapace of marine turtle species achieving the highest accuracy value of 100%. It could mean that colour feature is invariant of orientation and scale. Also, it is not vulnerable to illumination variations. In contrast, the techniques used to extract the shape and texture are sensitive to noise. Unfortunately, the networks NN_S, NN_T, NN_{S+T}, $*NN_S$, $*NN_T$, and $*NN_{S+T}$ over fitted, and NN_S, NN_T, $*NN_S$, and $*NN_T$ have had poor classification accuracy in predicting new images. It might be due to the limited number of instances in the dataset. More feature about the shape and texture should be extracted to create more discriminative information about the species. Also, effective techniques to select the region of interest, such as polygon or contour should be used to mitigate the noise issue. Therefore, the results do not mean that colour is a more important feature than shape or texture in recognising marine turtle species; they are equally important. They complement each other, and in cases where the colour cannot be used to classify, shape or texture can be used to determine the species.

In most of the cases, the networks created using original training sets outperformed the networks derived from the trial-error-test. It could be that the parameters used in trail-error-test were not sufficient to demonstrate the power of these networks. Interestingly, the results showed that the combination of the features could decrease or increase the accuracy value when the strong features are combined with weak characteristics, in contrast to what Anami et al. (2013) said that the combination of the features could only increase the accuracy. The results showed that the mix of delicate features could increase the accuracy rate. For example, the NN_{S+T} achieved an accuracy value of 85% compared to when NN_S and NN_T were trained solely achieving accuracy values of 75.5%, and 71%, respectively. Another example is $*NN_{S+T}$ achieved an accuracy value of 82% compared to when $*NN_S$ and $*NN_T$ were trained solely achieving accuracy values of 76.5%, and 70.5%, respectively. Overall, the networks enhanced the generalisation success rate when they were formed using the combination of any feature, which is confirmed with Rao et al. (2013).

Original		Trial-error-test	
Networks	ACC (%)	Networks	ACC (%)
NN_C	98	$*NN_C$	100
NN_S	75.5	$*NN_S$	76.5
NN_T	71	$*NN_T$	70.5
NN_{C+S}	98.5	$*NN_{C+S}$	98.5
NN_{C+T}	98.5	$*NN_{C+T}$	98
NN_{S+T}	85	$*NN_{S+T}$	82
NN_{C+S+T}	98.5	$*NN_{C+S+T}$	96

Table 4: Testing the networks generalisations abilities in the new dataset, where ACC means Accuracy.

One limitation of this research was the sample size. Clearly, 159 patterns are not enough to make generalisations about all species. The reason for the small training set is due to copyright issues, false labelling images, and incomplete information about the different species of marine turtles. However, from the results of a limited number of 159 instances, and the approaches used in this research, the models were favourable in recognising the patterns. So far, limited studies appear to have applied current knowledge of neural network to the field of pattern recognition of marine turtle species based on the characteristics of the carapace. The results demonstrate that the features extracted can be applied to develop a system for pattern recognition of marine turtle species.

IV. Conclusion

Colour outperformed shape and texture in recognising the species. Moreover, it was found that when the networks were trained using any combination with colour, the colour proved to have more influence in the recognition process. Further experiments should be done using more species. Also, studies are required to investigate the extraction of additional features on the shell.

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