Wild boar Classification by Using a Fusion of Texture Analysis Methods

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***Abstract*—In several countries the wild boar is an invasive species that remains widespread mainly due its adaptability and uncontrolled reproduction. The monitoring of populations of this pest by camera traps is a promising technique. These devices capture a large variety of animals, including native species that share similarities with the wild boar, therefore the precise identification of the animal species is essential to control the wild boars. To address this problem, we evaluated 18 different texture analysis methods on their ability to discriminate between two native "bush pigs" species of the Brazilian fauna, collared peccary (*Pecari tajacu*) and white-lipped peccary (*Tayassu pecari*), and one invasive species, wild boar (*Sus scrofa*). Results show that species identification is a difficult task due to the similarities among classes, being the distinction between native and invasive species an easier task, and that combining of texture methods improves the accuracy while it diminishes the number of false positives (i.e., native species classified as invasive).**

I. Introduction

The wild boar (*Sus scrofa*) is a species originally from Eurasia and thereafter spread due to human intervention, making it the most widespread swine [1]. The species is present in all continents, except Antarctica, either in the wild or the feral form [2], descending from escaped domesticated swines.

Despite overhunting and alterations in land use, the species remains widespread and abundant, being considered a pest in several countries, as result of its adaptability, uncontrolled reproduction [3], depredation on crops and possibility of disease contagion to other species [4], including native species of swine. In 2017, the Brazilian government published and it is executing a plan for the monitoring of wild boars [5].

A straightforward strategy for the task of monitoring is the use of camera traps. Such devices work 24 hours a day with the aid of infrared sensors during the night-time hours and use movement sensors to take pictures of wild animals or record videos.

Among the pictures taken, several species of wild animals are registered, producing large quantities of images every day. In special, we can mention two native species of "bush pigs" commonly found in almost the entirety of Brazilian territory: the collared peccary (*Pecari tajacu*) and the white-lipped peccary (*Tayassu pecari*). Both species are physically very similar to the invasive wild boar, therefore the precise identification of what animal is in a picture is essential to the control of wild boars.

Separating the wild boar from its similar counterparts is a difficult task, specially due the wide range of circumstances images such as the obtained from camera traps are subject to, e.g. due to noise, motion blur, low contrast, occlusions, cropped data, etc. Pattern classification, computational vision and image processing are essential on this task.

In this paper, we evaluate 18 texture analysis methods applied to the classification of the wild boar, as well as the native South American "bush pigs", the collared peccary and the white-lipped peccary, chosen according to aspects such as applicability, novelty and efficiency. Firstly, we use those methods to extract texture descriptors for each image belonging to the dataset. The number of descriptors varies from method to method. Afterwards, we approach the classification task of identifying the animal species using K-Nearest Neighbors (KNN), and Linear Discriminant Data (LDA) [6]. The paper organization is: in the Section II, we discuss the literature focused on identifying wild animals. Section III presents details of the dataset, and describes the texture analysis and classifiers adopted. Section IV presents and discusses our results. In Section V we present our concluding remarks.

II. Related Work

Animal identification is a recurrent theme in the literature of computer vision and image processing. In contrast to plant biology, the identification task is less complex, owing to the fact that animal species present well-defined morphological patterns. Indeed, this is a field with a great deal of attention.

Sharma and Shah [7] studied cow detection in images using Histogram Oriented Gradients (HOG). The effect of the distance from the animal to the capturing device is also explored. Another study that focuses on the detection of cows is ref. [8], in which Haar features are used along with cascade classification. In [9], the detection of wild animals used both shape and texture attributes extracted from animal heads. A new set of attributes is proposed, which the authors refer to as Haar of Oriented Gradients (HOOG), later used with an AdaBoost classifier to find the species.

Wildlife images from the Internet are classified in [10], where a segmentation step is combined to the responses generated by Gabor filters. The use of distinct attribute selection methods is also addressed. Ding et al. [11] use a convolutional neural network (CNN) to identify four species of fishes using a dataset obtained from the web.

In [12], Support Vector Machines (SVM) classified regions with distinct color patterns to identify elephants. The detection method of large animals in aerial images by [13] introduces a semi-supervised shape recognition approach employing the wavelet transform and fuzzy neural networks. In [14], the authors detect cattle from aerial images [14]. They achieved good results for different CNNs. Similarly, [15] applied CNNs for detecting wildlife animals from UAV aerial data. A CNN approach is also used by [16], where the task is the identification of individual pigs based on face recognition. The authors adopted Haar feature-based classifiers to detect physical characteristics such as face details and eyes, achieving an accuracy higher than 80% in the best case.

Deep learning techniques are used in [17] to classify animal species captured by camera traps. Such techniques successfully automated the task of labeling the images. In [18], shape analysis worked sucessfully for detecting of seals in thermal images. In [19], the authors detect bears based on shape and movement attributes.

As we can see from the literature, computational techniques allow that several features, not manually possible to measure practice, extracted and then used to identify and classify animal species. Such attributes extend and improve the information about the dataset, yielding to a more effective identification. To the best of our knowledge, the environmental issue of the spreading of both the wild boar and its feral form is not yet discussed in the context of image processing, although some related works mention the species [20], [21]. Therefore, we believe this paper is the first to address the identification of wild boars and two of its similar but native counterparts, the collared and the white-lipped peccaries.

III. Material and Methods

A. Dataset

We collected for this study images of three different species of wild animals: the invasive wild boar (*Sus scrofa*); and the native collared peccary (*Pecari tajacu*) and white-lipped peccary (*Tayassu pecari*). Despite belonging to distinct families – the invasive species belongs to *Suidae* family, while both the native ones are representative of *Tayassuidae* family, all the three species present very similar appearance and behavior, making the visual identification of each species a given animal belongs to a difficult task, even for humans. Figure 1 illustrates how similar these animals are in appearance.

The dataset has 900 images, 300 for each species. Conditions are diverse, ranging from the capture device (e.g. camera trap, smart phone, etc.) to aspects such as noise, sharpness, dimensions and color information (e.g. colored, grayscale). We cropped the images to a size of 224×224 pixels, and considered them as RGB images, even in the case of the grayscale samples. We considered this image size as it was the minimum square region that could be cropped from some images withouth resizing them.

A human oracle – an expert – labeled all the images, classifying each one as either wild boar or its native counterparts. The entire dataset was checked to eliminate the presence of artifacts in the images.

B. Texture Analysis Methods

Over the years, researchers in the area proposed a vast number of texture analysis methods. Among them, we selected 18 methods based on their good results reported, wide range of applications and novelty. A brief description of each method follows:

- First-order: from the image histogram, we computed mean, variance, kurtosis, energy and entropy features, totaling 5 descriptors;
- Haralick [22]: this method uses the joint probability distributions between pairs of pixels at a given distance and direction to describe the image content. For this work we considered non-symmetric matrices with $\theta = \{0°, 45°, 90°, 135°\}$ and distances $d = \{1, 2\}$. Energy and entropy are computed from each matrix, totaling 16 descriptors;
- Fourier descriptors [23]: given an image, we applied the bi-dimensional Fourier transform. After applying the *shifting* operator over the resulting spectrum, we were able to compute 111 spectrum descriptors. We computed each descriptor as the sum of all absolute coefficients at the same radial distance from the center of the image;
- Gabor filters [24]: from the mathematical procedure and the parameter values proposed in [25], we created a set of filters applied over the input image, where each filter is obtained by modulating a 2D Gaussian function with a sinusoid with different orientations and frequencies. In the experiments we used 4 scales, 6 rotations, and lower and upper frequencies of 0.04 and 0.5, respectively, thus totaling 48 descriptors;
- Wavelet descriptors [26], [27]: from the input image we computed 3 dyadic decomposition using Daubechies 4. For each decomposition we computed energy and entropy from horizontal, vertical and diagonal detail coefficients, totaling 18 descriptors;
- Gray Level Dependence Matrix (GLDM) [28]: this method uses the frequency of occurrence of two pixels with a determined absolute difference in intensity given a specific distance and intersample space. In this work we used 4 distances ($(0, d)$,$(-d, d)$,$(d, 0)$, and $(-d, -d)$) and 3 intersample spaces (1, 2 and 5). Then, from each estimated probability-density function we computed 5 measurements (contrast, angular second moment, entropy, mean, and inverse difference moment), totaling 60 descriptors;
- Discrete Cosine Transform (DCT) [29]: from 3 1D DCT basis vectors ($U_1 = [1, 1, 1]^T$, $U_2 = [1, 0, -1]^T$, and $U_3 = [1, -2, 1]^T$) we computed 8 3×3 DCT masks. After

Fig. 1. Animal species in the dataset. From top to bottom row: wild boar (*Sus scrofa*); collared peccary (*Pecari tajacu*); white-lipped peccary (*Tayassu pecari*).

applying each mask to the input image we computed the local variance of the output, totaling 8 descriptors;

- Local Binary Patterns (LBP) [30]: this method describes a texture based on local binary patterns, which relates to the spatial configuration of local characteristics of an image. From these patterns, it is possible to compute histograms of their occurrences and use them as descriptors. In our experiments we used three different configurations, $(P, R) = \{(8, 1), (16, 2), (24, 3)\}$, thus leading to three histograms;
- Complex Network Texture Descriptor (CNTD) [31]: based on the complex network theory, this approach models a texture pattern as a network. A feature vector describes the texture by using the properties of the original network submitted to dynamic transformations. In this work, we used radius $r = 3$ to model the original network and generated 36 transformations. Then, we computed energy, entropy and contrast, thus resulting in 108 descriptors;
- Lacunarity [32]: initially proposed for binary images, and later extended to grayscale images, this method uses the spatial dispersion of gaps of a specific size to measure and describe a texture pattern. For the experiments we used a gliding-box with two threshold approaches (local and global). For each approach the number of thresholds was defined to maximize the accuracy in the dataset;
- Lacunarity 3D [32]: this method extends the gliding-box approach from lacunarity to analyze the gray level intensity as a third dimension of the image, thus computing the number of gaps in a 3D grid. Likewise to lacunarity, the number of thresholds was defined to maximize the accuracy;
- Fractal Descriptors from Local Binary Patterns (LBP+FD) [33]: This method combines image patterns obtained using LBP with Bouligand-Minkowski fractal dimension as a way to extract meaningful information from an input image. This approach computes $N = 11$ LBP patterns and it extracts 8 fractal dimension values from each, totaling 80 descriptors;
- Randomized Neural Network (RNN) descriptors [34]: this method uses local texture patterns to train an RNN, later using the weights of the output neuron layer to describe the original texture image. In this work, we used two approaches, with and without rotation invariance, totaling, respectively, 30 and 150 descriptors;
- Tourist Walk [35]: this algorithm considers the image pixels as cities explored by tourists. They can move from city to city by going to the nearest (or farthest) city not visited in the last μ time steps. Considering the specification described in [35], we were able to compute 48 descriptors.

C. Classifier

After computing the texture features from the image dataset, it is necessary to classify them in their respective classes. In this paper we evaluated two different approaches of classifiers: K-Nearest Neighbors (KNN) and Linear Discriminant Analysis (LDA) [6]. A brief description of each classifier follows:

- K-Nearest Neighbors (KNN): this is an instance-based classifier which uses a voting scheme to classify a sample. Given an input sample, this algorithm finds out the K closest samples from the training set based on a similarity metric and it attributes to the test sample the class present in most of the K selected samples. In our experiments, we used Euclidean distance as metric and $K = 1$ with standardized features;
- Linear Discriminant Analysis (LDA): this is a statistical classifier that uses the mean vector of each class and the covariance matrix of the dataset to compute hyperplanes that separate the samples into their respective classes.

For both classifiers we used leave-one-out as the validation scheme. This approach considers each single sample as a test set, while the remaining samples compose the training set. This procedure is repeated until all samples are used as test sets. At the end, we reported the number of test samples correctly classified as the accuracy of the method being evaluated.

IV. Results and Discussion

First, we evaluated each texture analysis method individually. We considered two scenarios: i) images classified according to the animal species (3 classes) and ii) images classified as wild boar or bush pig (2 classes). The LDA and KNN classifiers were also evaluated in both scenarios.

As we can see in Table I, LDA classifier presents a superior performance in most cases when compared with the KNN classifier and this difference of performance intensifies when dealing with wild boar/bush pig classification. We also noticed that classifying images into 2 classes is an easier problem than the species identification, given that all texture analysis methods present a substantially superior performance regardless of the classifier used.

Regarding the attribute used to discriminate the images, we noticed that the number of classes involved in the problem and the type of classifier affect the performance of each texture method, so that no method gets the best result in more than one test. More traditional methods (such as Gabor filters and GLDM) present better results when dealing with wild boar/bush pig classification, while more recent approaches are superior for species identification. A possible explanation for this lies in the fact that these approaches combine different types of attributes into a single feature vector. That is the case of LBP+FD method, which combines the analysis of local binary patterns (LBP) with complexity analysis by fractal dimension (FD).

We also evaluated whether combining of different texture analysis methods improves the accuracy in each scenario. Since we have 18 methods, it would be time-consuming to evaluate all 2^{18} combinations of methods. Thus, to the best combination we used Particle Swarm Optimization (PSO) [36]. This algorithm describes a solution of a given problem as a particle at position $[X(1), X(2), \ldots, X(D)]$ in the search space, where D is the number of dimensions. A measure of quality is also used to move the particles in the search space to improve a candidate solution. In our case, $D = 18$ is the number of dimensions (texture methods) in the search space and the measure of quality is the accuracy obtained by the classifier. During the execution of the PSO we considered that an i-th texture method is included in the combination of methods if $X(i) \geq 0.5$.

Table II shows the methods selected by PSO for each scenario. In general, we noticed that the KNN needs more methods, and so it produces a larger feature vector, to improve its classification result. Table III shows the results obtained from these combinations of methods. We noticed a small gain in the success rate regardless of the number of classes and the classifier used. However, this gain follows a substantial increase in the number of attributes used, mainly for the KNN, where 5.56% gain in the success rate requires $9.1\times$ more attributes.

Another important aspect of our problem refers to the number of false positive (i.e., collared peccary or white-lipped peccary classified as wild boar). For our given problem, the false positives must never occur (ideal case) or occur with a very low probability, while it is tolerant of false negatives (i.e., wild boar classified as collared peccary or white-lipped peccary). Figures 2 and 3 show the confusion matrices obtained for the best single method and best combination of methods for problems involving three and two classes, respectively.

When we consider the task of identifying of the animal species (3 classes problem), the KNN classifier produces a slightly lower rate of false positives, despite presenting a lower accuracy than the LDA. Differently, for the problem involving the wild boar/bush pigs classification, the LDA classifier presents a substantially better result.

V. Conclusion

This paper addressed the problem of "bush pigs" identification in real-world footage. During the experiments we considered two native species of the Brazilian fauna, collared peccary (*Pecari tajacu*) and white-lipped peccary (*Tayassu pecari*), and one invasive species, wild boar (*Sus scrofa*). We evaluated the performance of different texture methods in two scenarios: to identify the correct animal species and to discriminate only between native and invasive species. Results showed that the discrimination between native/invasive species is an easier task than the identification of the species and that combining texture methods improves the accuracy while decreasing the number of false positives (i.e., native species classified as invasive ones). As future work, we intend to test more texture analysis methods and how they perform when in combination with other methods, as also other classifiers, such as SVM.

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TABLE I
SUCCESS RATE OBTAINED FOR EACH TEXTURE ANALYSIS METHOD IN EACH ANALYZED SCENARIO. METHOD MARKED WITH * MEANS THAT THE NUMBER OF FEATURES WAS DEFINED TO MAXIMIZE THE ACCURACY.

		3 Classes		2 Classes	
Method	# descriptors	LDA	KNN	LDA	KNN
First Order	5	45.44	41.67	66.67	60.67
Haralick	16	49.00	45.33	70.44	65.33
Fourier descriptors	111	47.67	42.22	65.89	61.78
Gabor filters	48	56.44	58.22	72.22	**68.44**
Wavelet descriptors	18	52.78	53.56	68.44	67.56
GLDM	60	59.89	52.22	**73.44**	67.67
DCT	8	48.67	48.89	67.00	63.56
LBP ($R = 1$)	8	48.78	44.78	66.56	62.78
LBP ($R = 2$)	16	49.56	51.44	68.22	67.89
LBP ($R = 3$)	24	48.33	49.78	67.67	64.89
CNTD	108	57.78	55.67	73.33	67.00
Lacunarity (local)	*	42.44	40.11	66.78	59.22
Lacunarity (global)	*	44.22	38.44	66.89	58.22
Lacunarity 3D	*	53.11	43.89	66.33	60.78
LBP+FD	80	**64.89**	54.33	72.89	66.11
RNN descriptors	150	51.89	59.22	69.67	70.78
RNN (rotation invariance)	30	62.78	**62.67**	71.44	74.33
Tourist walk	48	53.89	50.44	69.44	66.78

Fig. 2. Confusion matrices computed when considering the classification of animal species.

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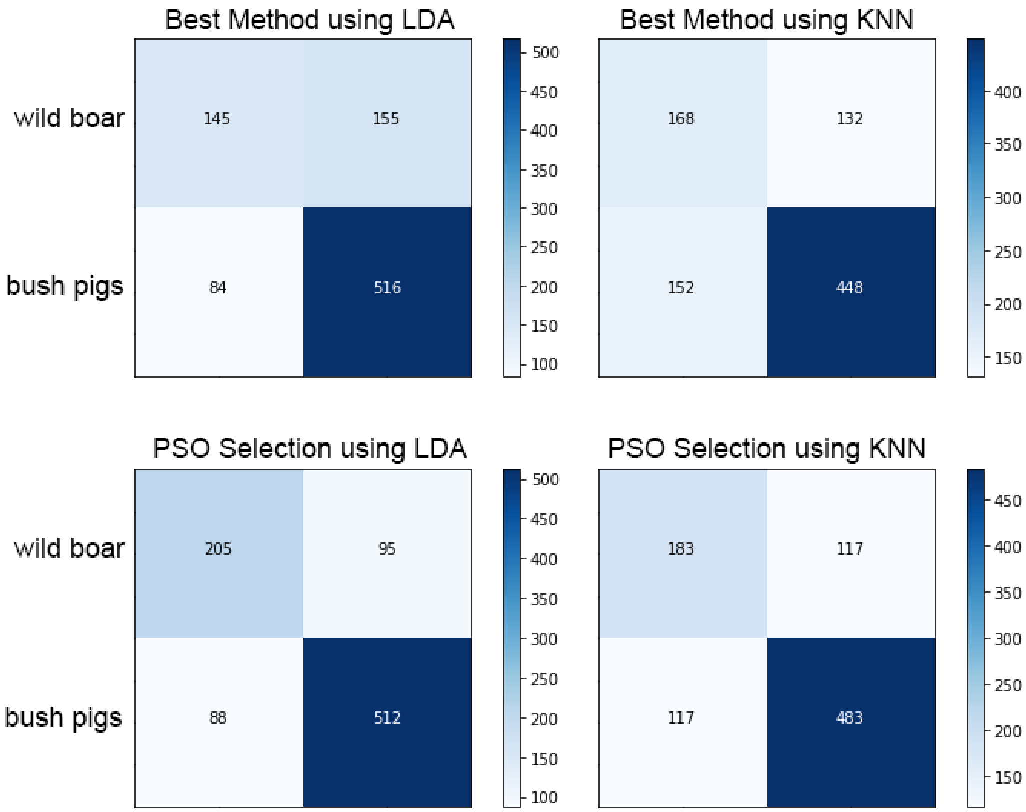

Fig. 3. Confusion matrices computed when considering wild boar/bush pig classification.

TABLE II
TEXTURE ANALYSIS METHODS SELECTED BY PSO ALGORITHM IN EACH ANALYZED SCENARIO.

	3 Classes		2 Classes	
Method	LDA	KNN	LDA	KNN
First Order	X			X
Haralick			X	X
Fourier descriptors				X
Gabor filters		X	X	X
Wavelet descriptors				
GLDM	X			X
DCT		X		
LBP ($R = 1$)		X	X	X
LBP ($R = 2$)	X			X
LBP ($R = 3$)		X		X
CNTD		X	X	
Lacunarity (local)	X	X	X	X
Lacunarity (global)	X	X		
Lacunarity 3D				X
LBP+FD		X	X	X
RNN descriptors	X	X		X
RNN (rotation invariance)		X		X
Tourist walk		X		

TABLE III
SUCCESS RATE OBTAINED FOR THE COMBINATION OF TEXTURE METHOD AND THE BEST RESULT FOR A TEXTURE METHOD IN EACH SCENARIO.

	3 Classes		2 Classes	
	LDA	KNN	LDA	KNN
Success rate (Best Method)	64.89	62.67	73.44	68.44
# descriptors	80	30	60	48
Success rate (PSO)	68.56	67.33	79.67	74.00
# descriptors	126	523	263	438

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