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Advance in the bat acoustic identification systems based on the audible spectrum using nonlinear dynamics characterization

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ABSTRACT

Frequential and time lineal parameters have shown a good performance in the recognition of bat species and nowadays there are many works which obtain those characteristics very accurately. However, it is necessary to move forward and test the capabilities of other characterizations on bioacoustics successfully used in other fields. In this work the chaos theory, which is an area of nonlinear dynamics systems, is applied to bat acoustic identification. The database used in the evaluation consists of 50 bat calls of seven different classes extracted from a previous work. The combinations of linear and nonlinear parameters have resulted in an average error of 1.8%, improving the accuracy in 0.42%. The differences to identify between the most difficult species and the easiest ones have been reduced.

1. Introduction

Humans have been curious about bats since the beginning of ecology. Bats are the only mammals that can fly, are present in most terrestrial ecosystems and have an extraordinary ability to orient in the dark. However, we did not start trying to conduct censuses of their populations until the early 20th century, when we realized that they were essential to the conservation of natural areas where they lived. Researchers began by capturing and ringing the specimens in order to monitor their movements. This method, totally inefficient, fell into disuse when Donald Griffin discovered the principle of echolocation (Griffin, 1958). From this time forth, the recognition has been focused on acoustic identification.

Currently the acoustic bat identification is done manually so an automatic identification of bat species would allow biologists to save a lot of time (Waters, 2013). Biologists could focus on studying the ambient conditions which causes bat species migration and population changes instead of detecting those changes. Thus, not only researchers would save time but also they would reduce the costs of the actions they decide to undertake following the information analysis. A request of biologists for years is to monitor environmental conditions in real time and in a remotely form.

Echolocation calls present some difficulties. The most obvious obstacle is the restriction of using only calls in the search phase (Griffin, 1958), i.e., search echolocation calls must be distinguished from the approach and terminal calls. We should not overlook the fact that bats are social animals and getting a bat call without interferences from their peers is a difficult task. Also, all possible variations in the locutions of the same species must be considered. Echolocation calls can vary according to sex (Neuweiler et al., 1987) or age (Moss, Redish, Gounden, & Kunz, 1997) depending on the species. Selecting the appropriate habitat and getting the data are also important because the climate and the level of stress of the specimen can cause significant variations in the recorded audio (Xu et al., 2008). Besides, bats vary the position respect to the microphone causing distortion in the signals captured by the recording device (Kennedy, Price, & Fuller, 1977). Consequently, the Doppler effect may be significant (Hiryu, Katsura, Lin, Riquimaroux, & Watanabe, 2005).

The recognition process is carried out in three phases, parameterization, modeling and classification (Lopez-de-Ipina et al., 2013). The samples would be fully characterized either by the description of the spectrogram image, or by the analysis of the calls. Then, the biometric identification process based on the audio begins.

The common parameterization procedure consists of the extraction of physical characteristics of the echolocation calls (Brigham, Kalko, Jones, Parsons, & Limpen, 2002). These are easily obtained either from the audio signal, or from its Fourier transform (FT). This process should be made so that the extracted feature helps to

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Table 1
Results obtained in the state of the art.

Author	Number of classes	Model	Accuracy average (%)	Call collection
Jones, Vaughan, and Parsons (2000)	6	DFA	89	Hand segmentation
Lucas (2000)	34	GMM	54.6	Hand segmentation
Parsons (2000)	12	ANN	87	Automatic segmentation
Biscardi, Orprecio, Fenton, Tsoar, and Ratcliffe (2004)	8	MLR	96.7	Hand segmentation
		DFA	93.3	
Fukui, Agetsuma, and Hill (2004)	7	DFA	92	Hand segmentation
Obrist, Boesch, and Flückiger (2004)	26	DFA	75	Hand segmentation
Skowronski and Harris (2006)	5	GMM	99.4	Hand segmentation
		HMM	99.4	
Preatoni et al. (2005)	13	DFA	77	Hand segmentation
		CA	45	
		CART	41	
		ANN	64	
Corcoran (2007)	9	DFA	68.3	Hand segmentation
Redgwell, Szewczak, Jones, and Parsons (2009)	14	ANN	98	Hand segmentation
		DFA	73	
		SVM	87	
Armintage (2010)	8	RF	96	Automatic segmentation
		SVM	92	
		ANN	91	
		PCA-ANN	88	
		DFA	77	
Walters et al. (2012)	34	eANN	83.7	Hand segmentation
Agranat (2013)	17	HMM	88.8	Automatic segmentation
Rodríguez-San Pedro and Simonetti (2013)	4	DFA	87.4	Hand segmentation
Henríquez et al. (2014)	7	GMM	97.3	Automatic segmentation

DFA: discriminant function analysis;
ANN: artificial neural networks;
eANN: ensembles of artificial neural networks;
MLR: multinomial logistic regression;
GMM: Gaussian mixture model;
HMM: hidden Markov model;
CA: cluster analysis;
CART: classification and regression trees;
SVM: support vector machines;
RF: random forest;
PCA: principal component analysis.

identify the class and therefore differentiate it from the rest. Bat locutions are modulated tones that are distinguishable by physical characteristics, so it is logical to use the extraction of physical characteristics for identification. Nevertheless, the results of previous works based on this parameterization find problems when the number of species to identify grows (Table 1). In our previous work we introduced a new conversion of the signal that makes the parameterization easier. The next step is the use of new characterization sets. Because of the similarity between bat calls there are some other parameterizations susceptible of being used in this field.

The modeling process consists of groups of features from the same class in order to create mathematical representations of each class. Researchers have studied the benefits of countless parametric and nonparametric models for the classical parameterization (Britzke, 2003). It is a difficult task to conclude what is the optimal modeling process as the success depends on the other processes. In general it is not wrong to say that the more flexible models as Gaussian mixture models (GMM) or hidden Markov models (HMM) adapt better to the variations of the parameters of the same class (Britzke et al., 2011). Those models have behaved satisfactorily using our characteristic set.

The last step is classification, i.e., to relate an unknown sample to one of the classes represented by the models. This comparison returns a value of similarity which is a measure of how related are the parameters of the sample with respect to each model of each class obtained. The higher value corresponds to the greatest similarity between a model and a sample.

Table 1 shows the results obtained from previous works. Most of them employ a parameterization based on physical characteristics. It is also shown how the capacities of several models have been tested in some works. We also emphasize that only in Henríquez et al. (2014) an automatic unsupervised segmenter from recordings have used.

It is the time to rethink new strategies in bioacoustics which would allow us to move forward. Nonlinear measures are a new way to characterize the audio in a different way (Alonso, De León, Alonso, & Ferrer, 2001; Bahoura, 2001; Kumar, 1996). Chaos theory is an area of nonlinear dynamics systems theory and has been adopted as a nonlinear approach to speech signal processing in the last two decades (Alonso, Díaz-de-María, Travieso, & Ferrer, 2005; Henríquez et al., 2009; Maragos, Dimakis, & Kokkinos, 2002; Vaziri, Almasganj, & Behroozmand, 2010). The speech signal has been characterized by mean of complexity features studied such as dimension correlation (Jiang, 2002; Zhang, 2003), Rényi entropies (Henríquez et al., 2009), Lyapunov exponents (Alonso et al., 2005; Maragos et al., 2002) Hurst exponent (Vaziri, Almasganj, & Jenabi, 2008) or Lempel–Ziv complexity (Vaziri et al., 2010), among others.

In bat acoustic signals, there is evidence of nonlinear phenomena in vocal production (Fitch, Neubauer, & Herzel, 2002; Gadziola, Grimsley, Faure, & Wenstrup, 2012; Kobayasi et al. 2012). According to these research works, the mammalian vocalizations exhibit large variations in their spectrotemporal features. These works show that the change in laryngeal air flow yield several non-linear effects on sound production. Based on these studies, we propose the application of a set of nonlinear features to extract nonlinear characteristics of the bat acoustic signals. As per author's knowledge, this is the first time that nonlinear features are applied to acoustic bat signals. The results confirm that the proposed nonlinear