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INVESTIGATION ON THE POSSIBILITY OF USING ENTROPY APPROACH FOR CLASSIFICATION AND IDENTIFICATION OF FROG SPECIES

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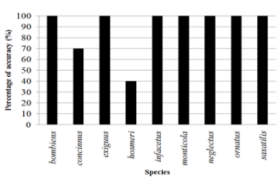
Graphical abstract



Performance of frog sound classification system using full entropy approach

Abstract

Animal species identification based on their sound has received attentions from researchers. This is to establish fast and efficient identification method. Identification of frogs have been one of the examples where research activities have shown some progress. Mel Frequency Cepstrum Coefficient (MFCC) and Linear Predictive Coding (LPC), coupled with *k*-th Nearest Neighbor (*k*-NN) or Support Vector Machines (SVM) have been the favorate approachs used by researchers. Quite recently, a new classification and identification method of sound using entropy-based approach for species identification of Australian frogs was proposed. Shannon, Rènyi and Tsallis entropy were used as features of extraction for the purpose of pattern recognition. Result shows that the full entropy-based animal sound identification system has successfully identified most of the frog species used in this study. The overall classification accuracy is as high as 91% with two failures from nine samples at 70% and 40%, respectively. A comparative analysis highlights the advantages of full entropy approach over conventional frequency spectral and hybrid methods. This is shown especially in the running time of a computer that required to complete the species identifications process. The result presented in this paper indicates that full entropy-based method can be used for faster frog species identification.

Keywords: Bioacoustics signal, entropy, frogs sound analysis, pattern recognition, specisis identification

Abstrak

Pengecaman spesis hawian berasaskan bunyi telah mendapat perhatian ramai pengkaji. Ini adalah untuk pembinaan satu kaedah pengecaman yang pantas dan berkesan. Pengecaman katak merupakan salah satu kajian yang telah menunjukkan kemajuan. Kaedah Mel Frequency Cepstrum Coefficient (MFCC) dan Linear Predictive Coding (LPC), yang dijalankan secara bersama dengan *k*-th Nearest Neighbor (*k*-NN) atau Support Vector Machines (SVM) merupakan pilihan utama para pengkaji. Tidak begitu lama dahulu, satu kaedah pengkelasan dan pengenalpastian bunyi berasaskan entropi untuk penentuan spesis katak Australia telah dicadangkan. Entropi Shannon, Renyi dan Tsallis telah digunakan untuk memperolehi cirian bagi mengenalpasti polanya. Keputusan menunjukkan bahawa kaedah berasaskan entropi sepenuhnya berjaya mengenalpasti hampir semua spesis katak dalam kajian. Ketepatan pengkelasan secara keseluruhannya adalah sehingga 91% dengan hanya dua kegagalan daripada sembilan sampel masing-masing pada 70% dan 40%. Analisis perbandingan telah menyingkap kelebihan kaedah entropi penuh berbanding kaedah lazim berasaskan spectra frekuensi dan juga hibrid. Ini ditunjukkan terutamanya dalam masa yang diperlukan oleh computer untuk menyiapkan proses mengenal sepsis berkenaan. Keputusan yang dipaparkan dalam kertas kerja ini menunjukkan bahawa kaedah berasaskan entropi sepenuhnya boleh digunakan bagi pengecaman sepsis katak yang lebih pantas.

Kata kunci: Isyarat bioakustik; entropi; analisis bunyi katak; pengecaman pola; pengecaman spesis.

1.0 INTRODUCTION

Biological classification is a taxonomic process used by biologists to classify living organisms. It is important for identification of unknown species, grouping of new organisms with existing ones, assigning names to organisms (nomenclature) and providing a common reference for those already identified.

Conventionally, living organisms are classified based on their morphological and behavioral. It was then evolved into the application of genetic and biochemical observations. Recently, it was shown that animal species can also be identified based on their calls when the animal sound is measured acoustically to relevant features [1-2]. For instance in birdsong, some species of bird e.g. Cardinalis produce songs with individual syllables that are almost pure tone while other birds such as cockatoos, however, have a truly chaotic waveform [3]. Many sound signal analysis methods have been suggested in the literatures to study the characteristics of the sound signal in a particular feature. They can be categorized into two groups-the frequency domain and the time domain [2]. Combination of these two categories is known as time-frequency analysis. Fourier transforms (FT) was once one of the most commonly used frequency domain method in animal sound analysis. It had been used to study the active frequency component in a sound signal. However, some information such as phase change in the signal cannot be detected by FT. Therefore, time-frequency analysis comes in to fill this gap and ever since it becomes the most frequently used approach. Among the techniques are the short-time Fourier transforms (STFT) and wavelet transforms. Time-frequency analysis has become the favorite method in literatures because the outputs are easier to visualize and to understand the behavior or pattern of the sound signals [4-5]. However, the shortcomings of this method are computationally intensive and energy and time consuming. Other available time domain methods are pulse distance density [6], temporal structure of the pulses, pulse length and zero-crossing rate [2].

Frogs have been identified as good biological indicators as the health of frogs signifies the conditions of an ecosystem [7-9]. Unfortunately, technique devoted to the development of automated frog sound recognition system is not widely known in the literature. Thus, it becomes essential to develop an effcient frog sound recognition system [1]. Several automated frog identification have been investigated such as using k-th Nearest Neighbor (k-NN) and Support Vector Machines (SVM) [1], Mel Frequency Cepstrum Coefficient (MFCC) with Support Vector Machines (SVM) identifier [10] and Linear Predictive Coding (LPC) with k-NN [11] with good accuracy.

Quite recently, a hybrid method that consists of spectral centroid (based on FT), Shannon entropy and Rényi entropy, as bioacoustics features had been introduced for animal species identification [12]. The study claims that the animal species can be identified in average up to 98% of accuracy based on the combination of those features. Since the hybrid method has given such encouraging result, the authors have further investigated the potential of pure entropy approach (Shannon, Rényi and Tsallis entropy) for bioacoustics signal analysis and animal species identification. They found that full entropy approach is inferior in detection accuracy [13]. This paper is an extension from the previous work with additional information on the analysis of advantages of the full entropy over the conventional and hybrid method.

2.0 THEORETICAL BACKGROUND

2.1 Shannon, Rényi And Tsallis Entropy

In order for an information measure to qualify to be an entropy in thermodynamic sense, it has to satisfy the four main Khinchin axioms as follow [14]. Axiom I states that the information measure I only depends on the probabilities pi of the events and nothing else. Axiom II states that information measure takes on an absolute minimum for the uniform distribution and any other probability distribution has an information contents that is larger or equal to that of the uniform distribution. Axiom III ensures that the information measure remains unchanged even if the sample set of events is enlarged by another event that has probability zero. Finally, Axiom IV postulates that the information measure should be independent of the way the information is collected, and in particular this axiom is essential to describe joint probabilities. The three definitions of entropy employed in this study, namely the Shannon entropy, Rényi entropy and Tsallis entropy would differ largely due to variation in additivity and convexity assumptions in Axiom IV.

Shannon entropy, S is the measure of information content in a sequence of signal, $X = \{x_1, x_2, x_3, \ldots, x_n\}$. Shannon entropy describes the average of all the information contents, I(p) weighted by their probabilities p_i, written in mathematical expression as

$$S = E[I(p)] = \sum_{i=1}^{n} p_i I(p_i) = -\sum_{i=1}^{n} p_i \log_2 p_i \quad (1)$$

where E[I(p)] denotes expectation value of I(p). The continuous version of the Shannon entropy is known the differential entropy given as

$$S = -\int_{-\infty}^{+\infty} p(x)\log_2[p(x)]dx \quad (2)$$

Shannon entropy can also be used to measure the degree of predictability of a signal. Consider for example a d.c. signal at constant amplitude k. Its probability density function is then a unitary impulse located at k, i.e. $pi = \delta(k)$, therefore its entropy or unpredictability is zero. Shannon entropy has been used in many applications including in biodiversity and in ecology [15-16].

By introducing less stringent condition which states that the entropy of independent systems should be additive, one can use Rényi entropy of order $q \geq 0$, defined as [17-18]

$$S_q^{(R)} = \frac{1}{1-q}\log_2\left(\sum_{i=1}^{n} p_i^q\right), \quad (3)$$

where pi is the probability of the occurrence $\{x_1, x_2, x_3, \ldots, x_n\}$ in the signal. Rényi entropy have been used in communication and coding theory [19] data mining, detection, segmentation, characterization of signals and sequences [20], signal processing [21], classification, image matching and registration [22]. Rényi information can be used to 'obtain different averaging of probabilities' via the parameter q [23]. By considering as a function of q, the spectrum of the Rényi entropy is also of some interest in many different fields. For example, Rényi information of order of q = 2 is used as a measure of diversity in economics [24]. In the study of random signal, a lower bound of Rényi entropy at least in the order of $q = 2$ is often adopted. Measurement of Rényi entropy also refers to the estimation of noise when transmitting a signal. One may expect that in this context, the 'highly ordered' animal sound signal will produce in relatively low complexity.

The Rényi entropy does not possess a definite convexity, which is crucial for formulating a generalized statistical mechanics. Hence, other candidates for information measures have been introduced and among the most notable is the Tsallis entropy (also known as q-entropy) written as [25]

$$S_q^{(T)} = \frac{1}{q-1}\left(1-\sum_{i=1}^{n} p_i^q\right) \quad (4)$$

where $q \in R$ is a real parameter which is also known entropic index. The Tsallis entropy is quite different to the Rényi entropy and this is noticeable from the expression that lacks the logarithmic term. However, the Tsallis and Rényi entropies are related through the following relation.

$$S_q^{(T)} = \frac{1}{1-q}(1-e^{(q-1)S_q^{(R)}}) \quad (5)$$

Tsallis entropy has been used in several studies, including measurement of complex systems in electric signals of ECGs and myocardial infarction [26], study of complexity of learning in both natural and artificial systems [27] and understanding nonlinear physiological signals [28].

2.2 *k*-NN CLASSIFIER AND ASSESSMENT OF PERFORMANCE

The non-parametric *k*-NN classifier is known as a simple yet powerful method for classification in pattern recognition, machine learning, data mining, and information retrieval [1]. It has been used in variety of sound analysis applications. Taking a set of parameters, *k*-NN searches the nearest neighbor among training data by using the categories of neighbor to consider the class of a given input.

In this study, the feature vector which consists of Shannon, Rényi and Tsallis entropy of the sound samples from each species were first determined and used as training data to represent each animal species. In the classification stage, given a set of parameters, it finds the nearest neighbour among training data and uses the categories of the neighbour to determine the class of a given input. The similarity between parameters is measured by using the distance metric method. There are different types of distance metric including Euclidean, city block, cosine, correlation and Hamming. For this study, Euclidean distance was selected as the distance metric methods for *k*-NN classifier in species classification. The Euclidean distance defines the distance $d(m,n)$ between instances m and n as [1] as

$$d(m,n) = \sqrt{\left(\frac{|y_{m1-n1}|}{R_1}\right) + \left(\frac{|y_{m2-n2}|}{R_2}\right)^2 + \ldots + \left(\frac{|y_{mi-ni}|}{R_i}\right)^2} \quad (6)$$

where $R_a = \max(y_a) - \min(y_a)$, which denotes the range of attribute a and used as normalization in order to avoid any attribute overpower the other attributes.

3.0 EXPERIMENTAL DETAIL

3.1 Full Hardware Setup

In this work, a database that consists of nine frog species found in Australia, as listed in Table 1 Frogs Australia Network, was used. The Microhylidae is a family of firmisternal frogs, which have broad sacral diapophyses, one or more transverse folds on the surface of the roof of the mouth, and a unique slip to the abdominal musculature. Almost all Australian Microhylids are small (snout to vent length less than 35 mm), and all have procoelous vertebrae, are toothless and smooth-bodied, with transverse grooves on the tips of their variously expanded digits. The terminal phalanges of fingers and toes of all Australian microhylids are T-shaped or Y-shaped with transverse grooves [29]. They produce sound by pneumatic generation where pneumatic air is forced between two membranes in the larynx in such a way to cause them vibrate at a very nearly their mechanical resonance frequency [30-31].

Table 1 Frog species for Microhylidae as test samples

Family	Scientific name	Common name
	Cophixalus bombiens	Buzzing Nurseryfrog
	Cophixalus concinnus	Tapping Nurseryfrog; Elegant Frog; Beautiful Nursery-frog
	Cophixalus exiguus	Dainty Nurseryfrog; Scanty Frog
	Cophixalus hosmeri	Rattling Nurseryfrog; Hosmer's Frog
Microhylidae	*Cophixalus infacetus*	Creaking Nurseryfrog; Inelegant Frog
	Cophixalus monticola	Mountain Nurseryfrog
	Cophixalus neglectus	Bellenden Ker Nurseryfrog; Neglected Frog
	Cophixalus ornatus	Ornate Nurseryfrog; Ornate Frog
	Cophixalus saxatilis	Black Mountain Boulderfrog; Rock Frog

The proposed method of species identification involves four stages. It begins with segmentation of the sound signal from the original recordings of the nine selected frog species. Figure 1 and Figure 2 show examples of how the segmentation of the syllable is performed with the corresponding spectrogram for *Cophixalus bombiens* and *Cophixalus saxatilis*, respectively. For each species, a total of 10 segments were prepared.

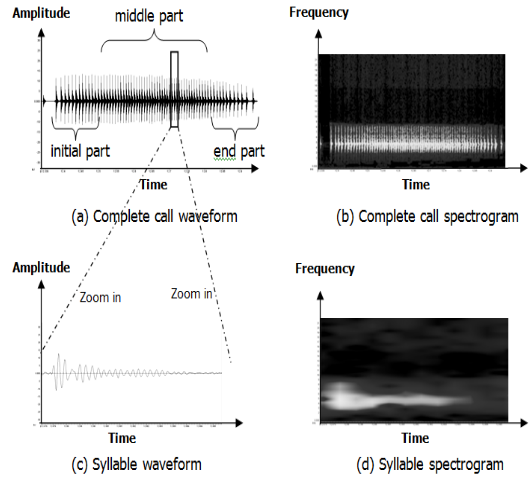


Figure 1 Example of complete call and segmented syllable for *Cophixalus bombiens* in time domain and the corresponding spectrogram

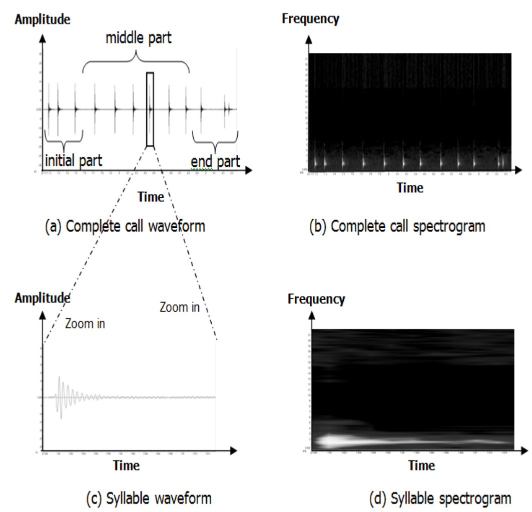


Figure 2 Example of complete call and segmented syllable for *Cophixalus saxatilis* in time domain and the corresponding spectrogram

A syllable is basically a sound that an animal produces with a single blow of air from the lungs [1]. Once the syllables have been properly segmented, a set of features can be calculated to represent each syllable. From Figure 1 and Figure 2, it can be seen that the waveforms of each syllable from a call looks similar. Depending on the species, the number of syllable in a call varies from as low as 12 syllables to as high as 96 syllables. The duration for each syllable is between 3.58 to 65 ms, whereas the duration for each call is in the range of 0.536 to over 3 s. The dominant frequency of the call for each species also varies from 1.7 kHz to 4.9 kHz with different active frequency range. In this study, the signal segmentation was performed using software 'Raven Lite'. The segmented syllables for each species are digitized in 24-bit WAV format with sampling frequency of 44.1 kHz. MATLAB software is used for feature extraction and classification analysis.

After segmentation, extraction of the features of the sound signal was then performed in the second stage. As previously mentioned, three types of entropy namely Shannon, Rényi and Tsallis entropy, were extracted from the syllable signal using (1), (3) and (4), respectively. In the present study, entropic index q = 2 is adopted for Rényi and q = 0.1 for Tsallis entropy due to their wide application in signal analysis.

In the third stage of the work, a set of reference data for each species was determined from the average of each feature. Using these training data and the entropy value of each by syllable as input, the species classification and identification were performed using *k*-th nearest neighbor (*k*-NN) algorithms given in (6).

The final stage of this work is the assessment of the accuracy of the proposed method. In order to examine its performance, the classification accuracy *A* is measured based on the percentage of the correctly identified syllables given by

$$A = \frac{N_c}{N_s} \times 100 \quad (7)$$

where N_C is the number of syllables which were correctly recognized and N_S is the total number of the syllables for each species (10 syllables in this study).

4.0 RESULTS AND DISCUSSION

Figure 3-5 show the values of Shannon, Renyi and Tsallis entropy, respectively, for each syllable of the respective frog species. The results show that the entropy values for each syllable from a particular species mostly deviated in small range, indicating a high similarity in terms of the syllable produced by the test subjects. The dispersion of all values from Shannon and Renyi entropy are less than 10 bits whereas for Tsallis entropy the values are in the interval of 100-500 bits. In Shannon and Renyi entropy, an interesting pattern was found that all species exhibited a similar range, as small as two decimals point. Among them *bombiens, neglectus* & *ornatus sp.* are showing the least deviation with approximately 0.02-0.08.

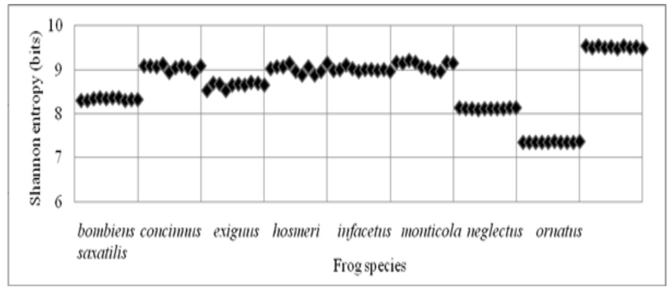


Figure 3 Shannon entropy of nine Microhylidae frog species for ten syllables each species

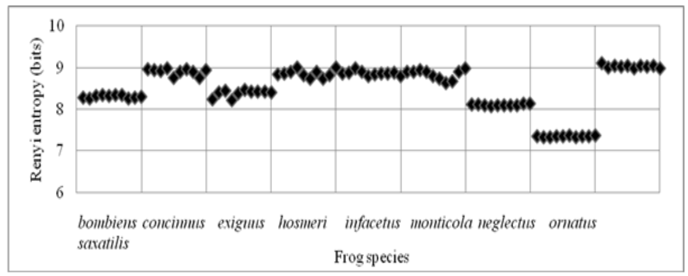


Figure 4 Rényi entropy of nine Microhylidae frog species for ten syllables each species

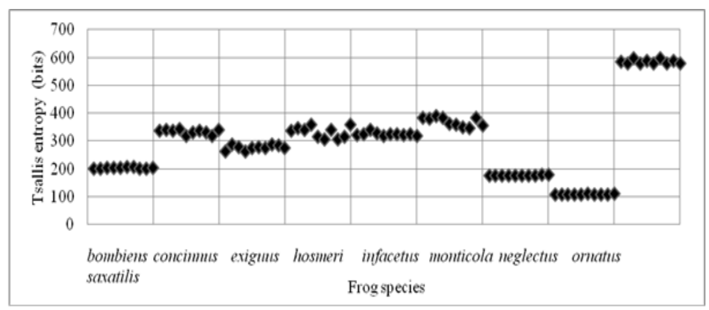


Figure 5 Tsallis entropy of nine Microhylidae frog species for ten syllables each species

Table 2 Training data for animal species identification

Frog species	Shannon entropy	Rényi entropy	Tsallis entropy
bombiens	8.34	8.30	203.00
concinnus	9.05	8.90	330.00
exiguus	8.60	8.40	270.00
hosmeri	8.90	8.85	340.00
infacetus	9.00	8.86	320.00
monticola	9.10	8.75	350.00
neglectus	8.11	8.10	175.00
ornatus	7.35	7.35	108.00
saxatilis	9.50	9.00	580.00

A slightly different pattern was observed in Tsallis entropy such that the range differs in the units of ones to tens. For example, most of the values of Tsallis entropy for ornatus sp. are in the interval of 107.69-108.91 bits but other species e.g. hosmeri sp. exhibited a relatively larger range of data with 304.30-358.73 (Figure 5). Due to this fact, the average value for the features of each species is used as the training data which is shown in Table 2. For example, the training data for bombiens-Shannon entropy in Table 2 (the value in column 2 raw 2) is the average value from all the Shannon entropy given in column 1 of Figure 3. The number of successfully identified syllables NC (refer to (7)) was determined based on the number of syllables that are correctly classified into right species using k-NN in (6) with data in Table 2 as reference for the related species.

Figure 6 shows the performance of the proposed method in terms of percentage of accuracy. It should be noted that the percentage of accuracy above 80% is considered successful. It can be seen that seven of the species were successfully identified with 100% accuracy. The proposed method had successfully identified the uniqueness of these species. Only *Cophixalus concinnus* and *Cophixalus hosmeri* are failed to be recognized with 70% and 40% of accuracy, respectively. Detailed inspection of Figure 3, 4 and 5 shows that the entropy features for these two species are very close resemble to each other. This has made it difficult to identify or differentiate each sound correctly.

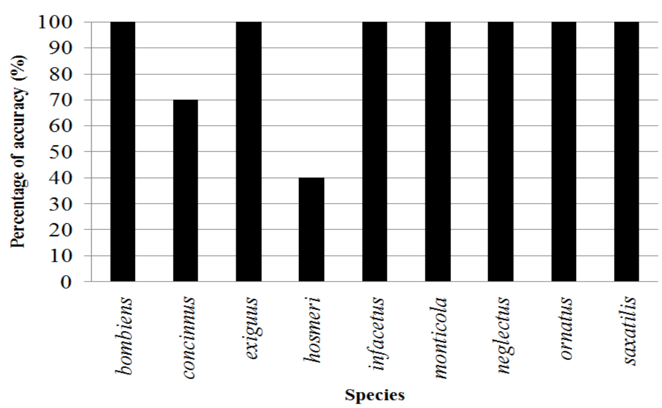


Figure 6 Performance of frog sound classification system by using entropy approach for nine Microhylidae frog species

As a comparison with spectral centroid method, the pure entropy approach has marked significant improvement in the accuracy of classification [12]. It has decreased the failures of identification to two species with an average of more than 91% in accuracy. This is slightly low compared to the hybrid method previously reported. Therefore, further analysis was performed in terms of running time of the identification process on Intel i3 and i5 processors with standard specifications. Running time is one of the important factors for a practical implementation of an identification method. It was found that the CPU running time reduced by 25% compared to hybrid method. The overall comparison between the three methods is shown in Table 3 and favors the full entropy method in general.

Table 3 Comparison of performance between spectral centroid, pure entropy & hybrid classification method

	Spectral centroid method	Pure entropy method	Hybrid method
Accuracy	65%	91%	98%
CPU time	<40%	<25%	-
Failure of identification	6 sp.	2 sp.	none

5.0 CONCLUSION

A set of sound recordings from nine Microhylidae frogs were collected and segmented into syllables form used as test samples. Three different entropy approaches, which are Shannon, Rényi and Tsallis, were then extracted from the test samples and used as acoustical features for animal species identification. Based on these entropy features, the *k*-NN classifier managed to recognize majority of the Microhylidae frog species with high recognition rate. The low computational complexity of full entropy approaches have given an advantage of being implementable on low power microcontrollers leading to the possibility of hand-held recognizers for long term bioacoustics monitoring.

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