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An Extensive Survey of Bat Species Identification based on Acoustics

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***Abstract*— Bat, the only flying mammal, is a very important keystone member in the ecosystem and it plays a vital role in maintaining eco-balance through propagation of vital flora and pest management in the forest, which is the major indication for biodiversity conservation. Bats are also the key informers of climate change impact on their habitat. Bat species and their activity are made use of to assess habitat quality and they serve as biological indicators of the ecosystem conditions and degradation. Many of the ideas expressed in this research work have been published in international journals. Bat species diversity and their impact in the habitat are studied using various techniques including speech recognition, voice recognition, artificial neural networks etc and to detect the presence of bats acoustically. In this paper, the various computer techniques used to study bats are surveyed.**

Keywords*— bats, echolocation call, acoustic survey, artificial neural networks, support vector machine.

I. Introduction

India has an incredible diversity of bats. In the tropical region, fruit and nectar feeding bats play a vital role in the survival and re-growth of the rainforests. Fruit-bats spread seeds as they fly and digest their food. Nectar feeding bats pollinate many valuable plants such as banana, avocado, date, fig, mango etc. Insect-eating bats do pest management. Bats are not blind, but in addition to sight, many species have highly developed ultrasonic bio-sonar capabilities, referred to as "echolocation", which they use to navigate and catch insects in total darkness. India holds one hundred and twenty bat species representations. Among them forty three are represented from Kalakad Mundanthurai Tiger Reserve[KMTR] of which six species are frugivores and the rest are insectivores. The fourteen types of forests of KMTR serve as the abode for the diversified species.

Kalakad Mundanthurai Tiger Reserve[KMTR], is located in the Western Ghats which is one of the biodiversity hotspots and also declared as "world heritage centre" by the UNESCO. KMTR has a coverage of 895 Sq.kms (Coordinates : latitude 8° 25' and 8° 53' N and longitude 77° 10' and 77° 35' E.). KMTR comprises of twelve major forest types to sustain biodiversity including bat species. The annual precipitation in this area is 3,500 mm.

Bats emit calls from about 12 kHz to 160 kHz, but the upper frequencies in this range are rapidly absorbed in air. Many bat detectors are limited to around 15 kHz to 125 kHz at best. Bat detectors are available commercially and also can be self-built. Some early bat detectors used ex-Navy, low frequency radio sets, simply replacing the aerial with a microphone and pre-amplifier. A bat detector is a device used to detect the presence of bats by converting their echolocation ultrasound signals, as they are emitted by the bats, to audible frequencies, usually about 300 Hz to 5 kHz.

Audio signals are generally referred to as signals that are audible to humans. Audio signals usually come from a sound source which vibrates in the audible frequency range. There are many ways to classify audio signals. An audio stream can be segmented into many categories such as silence, environmental sound, music and speech. Acoustics is a branch of Physics that studies sound. Audio data is an integral part of many computer and multimedia applications. Audio recordings are dealt with in audio and multimedia applications. The effectiveness of their deployment is dependent on the ability to classify and retrieve the audio files in terms of their sound properties. Rapid increase in the amount of audio data demands for a computerized method which allows efficient and automated content-based classification. Acoustic surveys are widely used for describing the prevalence of bats and activity patterns and are very important for habitat management and to assess the quality of a habitat[1].

A bat call library is a database in which there are acoustic details of all species of bats in a region, specifying the frequency range of the calls, shape of the calls etc. There are call libraries for European bats[2] and in other continents too.

The Megabats or the fruit-eating bats do not echolocate but the micro bats or the insect-eating bats use echolocation much..

II. Bat Species Identification Systems

The term 'Echolocation' was first coined by Donald Redfield Griffin to describe how bats use echoes of sounds they produce to locate objects in their path [3]. Echolocation[4], also called bio sonar, is the biological sonar used by several kinds of animals including bats. By producing short ultrasonic calls through their mouth or nose, bats trigger echoes from reflective surfaces for both orientation and object analysis[5]. Echolocating animals emit calls out to the environment and listen to the echoes of those calls that return from various objects near them. They use these echoes to locate and identify the objects. Echolocation is used for navigation and for foraging [6,7] (hunting, resting, feeding etc.) in various environments. Only insectivorous [8, 9] bats use echolocation. Bats produce ultrasonic sounds for the purpose of moving about in the darkness. They send the ultrasonic sound as an echo which may hit any obstruction and return back to the bat, implying that there is an obstruction ahead. This is called echolocation call.

Walters et.al.[2] have said that a call library contains recordings from a variety of methods and surroundings providing confidence to classify the variations represented in the calls. To ensure correct classification, the best quality calls within a recorded sequence can be taken into account. They have proposed a continental-scale tool for acoustic identification of European bats. They found that the use of acoustic methods at continental scales can be hampered by the lack of standardized and objective methods to identify all species recorded. They developed a continental-scale classifier for acoustic identification of bats, which can be used throughout Europe to ensure objective, consistent and comparable species identifications. They selected one-thousand-three-hundred-and-fifty full-spectrum reference calls from a set of fifteen-thousand-eight-hundred-and-fifty-eight calls of thirty four European species, from EchoBank, a global echolocation call library. They assessed twenty-four call parameters to evaluate how well they distinguish between species and used the twelve most useful, to train a hierarchy of ensembles of artificial neural networks to distinguish the echolocation calls of these bat species. Calls are first classified to one of five call-type groups, with a median accuracy of 97 6%. The median species-level classification accuracy is 83 7%, providing robust classification for most European species, and an estimate of classification error for each species.

Identification of bats from their calls can be split broadly into two paradigms: Qualitative and Quantitative. Qualitative methods involve researchers listening to calls [13], taking account of the echolocation call structure [10]. These methods require that the researcher has to get a good site(a suitable habitat) in which they can see the bats and record the echolocation calls. Hence the observer must wait for the opportunity to identify a bat and identify its staying place which is called the roost[13]. The researcher must follow the bats along flight paths to roosts where bats can be captured. These methods require several field visits and a lot of time; multiple observers may need to survey multiple sites simultaneously. Qualitative methods rely heavily on observer experience.

Vaughan et.al.[10] have done multivariate analysis of echolocation call parameters for the identification of British bat species. They presented a method for the identification of bat species from time-expanded broad-band recordings of their echolocation calls and suggested that the method may be used for the assessment of habitat use by bats. They placed British bats in three groups according to the structure of their calls: high duty cycle FM/CF/FM bats (Rhinolophus spp.), low duty cycle FM bats (Myotis spp. and Plecotus spp.) and intermediate duty cycle FM/CF bats (Pipistrellus and Nyctalus spp. and Eptesicus serotinus).

Wickramasinghe et.al.[11] have found that Bat activity was quantified using acoustic surveys within specific habitats on farms in southern England and Wales. Eighty-nine per cent of bat passes were identified to species level using artificial neural networks (ANN). A further nine percent were identified to genus. The dominant species on both farm types were Pipistrellus pipistrellus and Pipistrellus pygmaeus. Significantly more passes of Myotis species were recorded on organic farms than on conventional farms. This difference was also significant when water habitats were considered alone.

The echolocation calls of bats (call structure and shape of calls)[10] differ from species to species, that is, species-specific[11]. This facilitates acoustic identification of bat species. However, call structures within species can be extremely flexible and depend on factors including habitat, age, sex and the presence of conspecifics.[10,2]

Murray et.al.[12] have studied the variation in search phase calls of bats. Although echolocation calls of most bats exhibit species-specific characteristics, intraspecific variation can obscure differences among species and make reliable acoustic identification difficult. Levels of intraspecific variation in search-phase calls of 7species of vespertilionid bats from several locations in the eastern and central United States were examined. Echolocation calls were recorded from light-tagged bats using the Anabat II detector and associated software. Analook software was used to calculate values for 5 parameters of calls: duration, maximum frequency, minimum frequency, frequency of the body, and slope of the body. Analysis of our results indicates that most intraspecific variability in calls was attributable to differences among individuals and within individual call sequences. Observed levels of geographic variation, although significant in all species examined, were comparatively small and showed no trends among areas. They also included a preliminary description of variability in echolocation calls of Nyticeius humeralis and Myotis leibii.

Russo and Jones [13] have proposed identification of twenty-two bat species(Mammalia: Chiroptera) from Italy by analysis of time-expanded recordings of echolocation calls. They described the spectral and temporal features of echolocation calls emitted by twenty two bat species from Italy (three rhinolophids, eighteen vespertilionids and the molossid Tadarida teniotis). They examined time-expanded recordings of calls from nine hundred and fifty bats of known identity. Rhinolophus ferrumequinum, R. hipposideros, R. euryale and T. teniotis could be identified by measuring the call frequency of highest energy (FMAXE). They applied quadratic discriminant function analysis with cross-validation to calls from the remaining eighteen species. A function based on start frequency (SF), end frequency (EF), FMAXE and duration (D) provided a correct overall classification of approximately eighty two percent. They put forth a classification model at genus level that also comprised middle frequency (MF) and inter-pulse interval (IPI) that reached ninety four percent correct classification. They also devised two separate discriminant functions for species emitting FM (frequency modulated) and FM/QCF calls (i.e. calls consisting of a frequency-modulated component followed by a terminal part whose frequency is almost constant) respectively. The former function included SF, EF, FMAXE and D and provided an overall classification rate of 71%; the latter comprised EF, MF, D and IPI, and reached 96%. The functions can be applied to bat habitat surveys in southern Italy since they cover most of the species occurring in the area

A decision tree was used to classify zero-crossed echolocation call recordings from eight Australian species [14]. Machine learning techniques which are used in automated(human) speech recognition[15,16] have been used to detect and classify calls from five North American bat species. These methods allow satisfactory identification of several species.

Sound event classification is attracting a growing attention recently in the field of acoustic signal analysis[17]. An acoustic survey is one of the research methods of gathering information on the abundance of a species and detecting their presence using acoustic detectors. Acoustic surveys are carried out in a wide range of habitats to detect large number of species.

Support Vector Machines(SVM) [18-20], Artificial Neural Networks(ANN) [21] and Synergetic Pattern Recognition [22] are the frequently used to classify bats. Redgwell et.al.[18] have classified the echolocation calls of fourteen species of bats by support vector machines and ensembles of neural networks. Calls from fourteen species of bat were classified to genus and species using discriminant function analysis (DFA), support vector machines (SVM) and ensembles of neural networks (ENN). They found that both SVMs and ENNs outperformed DFA for every species while ENNs (mean identification rate– 97%) consistently outperformed SVMs (mean identification rate – 87%). Correct classification rates produced by the ENNs varied from 91% to 100%; calls from six species were correctly identified with 100% accuracy. Calls from the five species of Myotis, a genus whose species are considered difficult to distinguish acoustically, had correct identification rates that varied from 91 – 100%. Five parameters were most important for classifying calls correctly while seven others contributed little to classification performance.

Neural networks have also been used to identify species of British bats flying over organic and conventional farms. Although these previous studies accurately classify many of the species on which they are trained and prove the concept and value of quantitative call identification, they have not been made publicly accessible and are restricted to a regional(often national) level (eg. Venezuela[8]; Greece; Italy [13]; Meditteranean area[23]; UK [24]; Switzerland [22];). Therefore, they cannot be used to generate comparable classifications at a continental scale[2]. For continent-wide survey and monitoring programmes that aim to assess changes in activity over time or between sites, a quantitative method of identification that is objective, standardized and repeatable is essential.

Orbist M K et.al. [22] have found a variability in echolocation call design of twenty six Swiss bat species and have put forth the consequences, limits and options for automated field identification with a synergetic pattern recognition approach. They used pattern recognition algorithms for recognizing bat species by their echolocation calls. Automated systems like synergetic classifiers may contribute significantly to operator-independent species identification in the field. It necessitates the assembling of an appropriate database of reference calls. They presented data on species-specific flexibility in call parameters of all Swiss bat species (except Nyctalus lasiopterus and Plecotus alpinus). They found that the selection of “training-calls” for the classifier is crucial for species identification success, in the context of echolocation call variability differing between species and its consequences for the implementation of an automated, species specific bat activity monitoring system.

Jennings et.al. [25] have put forth their findings of human vs machine, in the identification of bat species from their echolocation calls by humans and by artificial neural network. Automated remote ultrasound detectors allow data on bat presence and activity to be collected. Processing of data involves identifying bat species from their echolocation calls. Automated species identification has the potential to provide consistent and potentially higher levels of accuracy than identification done by humans. Identification done by humans permits flexibility and intelligence in identification. The authors compared humans with artificial neural networks in their ability to classify recordings of bat echolocation calls of variable signal-to-noise ratios. These sequences are typical of those obtained from remote automated recording systems that are used in large-scale ecological studies. In this work, they presented forty five recordings produced by known species of bats to artificial neural networks and to twenty six human participants with one month to twenty three years of experience in acoustic identification of bats. Humans classified eighty six percent of recordings to genus and fifty six percent to species. Artificial neural networks correctly identified ninety two percent and sixty two percent respectively. There was no significant difference between the performance of artificial neural networks and that of humans. But artificial neural networks performed better than about seventy five percent of humans. There was little relationship between the experience of human participants and their classification rate. However, humans with less than one year of experience performed worse than others. Currently, identification of bat-echolocation calls by humans is suitable for ecological research. However, improvements to artificial neural networks and the data that they are trained on may increase their performance to those demonstrated by humans in future.

TABLE I SUMMARY OF STRONG POINTS AND LIMITATIONS OF PROPOSED TECHNIQUES AND FRAMEWORKS

Effort	Techniques Proposed	Strong Point
1	A practical sampling design for acoustic surveys of bats.	Acoustic surveys are very important for habitat anagement and to assess the quality of a habitat
2	A continental-scale tool for acoustic identification of European bats.	A bat call libraries are defined
3	Bat Echolocation Research: tools, techniques and analysis	Describes how bats use echoes of sounds they produce to locate objects in their path
4	Echolocation-producing short ultrasonic calls	The communicative potential of bat echolocation pulses.
5	Coordination of bat sonar activity and flight for the exploration of three-dimensional objects.	Bats trigger echoes from reflective surfaces for both orientation and object analysis
6	Foraging activity of bats in historic landscape parks in relation to habitat composition	Echolocation is used for navigation and for foraging
7	Spatial orientation and food acquisition of echolocating bats	Bats use echoes to locate and identify the objects and for foraging (hunting, resting, feeding etc.) in various environments
8	Recognition of species of insectivorous bats by their echolocation calls.	Only insectivorous bats use echolocation.
9	Contribution of acoustic methods to the study of insectivorous bat diversity in protected areas	Insectivorous bats produce ultrasonic sounds which may hit any obstruction and return back to the bat
10	Identification of British bat species by multivariate analysis of echolocation calls.	Multivariate analysis of echolocation call parameters- from time-expanded broad-band recordings of their echolocation calls-using call structure and shape of calls
11	Bat activity and species richness on organic and conventional farms: impact of agricultural intensification	Echolocation calls of bats differ from species to species, that is, species-specific
12	Variation in Search Phase Calls of Bats.	Intraspecific variation can obscure differences among species and make reliable acoustic identification difficult
13	Identification of bat species by analysis of time-expanded recordings of echolocation calls	Spectral and temporal features of echolocation calls emitted by bat species
14	Identification of bat echolocation calls using a decision tree classification system	Classify zero-crossed echolocation call recordings
15	Acoustic detection and classification of microchiroptera using machine learning: lessons learned from automatic speech recognition.	Machine learning techniques which are used in automated(human) speech recognition
16	Efficient Discrete Tchebichef on Spectrum Analysis of Speech Recognition.	Discrete Tchebichef Transform outperforms Fourier Transform and Fast Fourier Transform
17	Semi-supervised learning helps in sound event classification.	Sound event classification in acoustic signal analysis. Acoustic survey by detecting the presence of bats using acoustic detectors.
18	Classification of echolocation calls by support vector machines and ensembles of neural networks.	Support vector machines for the acoustic identification
19	Content-based audio classification and retrieval by support vector machines	Classification of sounds acoustically using support vector machines
20	Mixed type audio classification with support vector machine	SVM-based audio classification for music, speech, environment sound, speech mixed with music and music mixed with environment sound
21	Acoustic identification of echolocating bats by discriminant function analysis and artificial neural networks.	Echolocation calls were digitised- one temporal and four spectral features were measured from each call
22	Variability in echolocation call design of bat species	Consequences, limits and options for automated field identification with a synergetic pattern recognition.
23	Use of foraging habits by bats (Mammalia: Chiroptera)	Type of foraging habits determined by acoustic surveys: conservation implications.
24	Acoustic Bat Monitoring Programme	Quantitative bat call identification
25	Human vs machine: identification of bat species from their echolocation calls by humans and by artificial neural network.	Machines with artificial neural networks’ advantages and disadvantages on comparison with human beings

III. CONCLUSION

Acoustic monitoring is one of the powerful techniques for learning the ecology of bats. Acoustic surveys are used for identifying the occurrence of bats, their habitat management and activity patterns. Several researchers have carried out studies on bats in various parts of the world using several techniques such as artificial neural networks, speech recognition, voice recognition, pattern recognition algorithms, support vector machines, artificial intelligence etc. In this paper, we have carried out an extensive review on the various techniques used to identify and classify bats using their species-specific echolocation calls, which will be useful for the on-going and future researchers for their study in this area.

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