International Journal of Innovative Research in Advanced Engineering (IJIRAE)
Volume 1 Issue 1 (March 2014)

Bat Classification based on Perceptual, Spectrum and Cepstral Features in Kalakad Mundanthurai Tiger Reserve

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Abstract— Bats are the only mammals that can fly and are the keystone member to sustain biodiversity. Bats are present throughout the world, performing vital ecological roles of pollinating flowers and dispersing fruit seeds. Bat is a very important 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. Bats are important as they consume insects, pests, reducing the need for pesticides. Bats give major indication for biodiversity conservation. Bats are also the key informers of climate change and its impact on their habitat. Many tropical plant species depend entirely on bats for the distribution of their seeds. About seventy percentage of the bat species are insectivores. The rest are frugivores or fruit-eaters. Monitoring of bat activity is useful to assess habitat quality. Bats serve as biological indicators of the condition of the ecosystem and its degradation. The insectivorous bats use echolocation calls, making it possible to detect the prevalence of bats through acoustic detection methods. The echolocation calls are species-specific. Hence, acoustic identification and classification of bat species are probable. In this paper, a bat classification method using perceptual, spectrum and cepstral features is proposed. Sixteen species of bats that are present in the Kalakad Mundanthurai Tiger Reserve are taken into consideration.

Keywords— bats, echolocation, foraging, acoustic, bat activity, species identification.

I. INTRODUCTION

Bats are unique among mammals as they are the only group to have evolved true powered flight. They belong to the order Chiroptera, whose forelimbs form webbed wings, making them capable of sustained flight. Bats can propel themselves with their wings and fly for long periods. Bats are nocturnal and usually spend the daylight hours roosting in caves, rock crevices, trees or man-made structures. Activity begins around dusk, when bats leave the day-roost and start feeding. Many bats remain at their feeding sites until just before dawn when they return to the day roost.

Bats are present all over the world, performing vital ecological roles of pollinating flowers and dispersing fruit-seeds. Many tropical plant species depend on bats for the distribution of their seeds which helps in the survival and re-growth of forests. About 70% of the bat species are insectivores and the rest are frugivores or fruit-eaters. The insectivores consume insect pests and thus do the function of pest management in the agro and forest ecosystems. Diversity of bat species and their impact in the habitat are studied using various techniques such as voice recognition and artificial neural networks to detect the presence of bats acoustically. One hundred and twenty bat species are available in India, out of which about forty three species are found in the KMTR region. The fourteen types of forests that exist in KMTR area serve as the abode for the diversified species of bats.

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 coverage of 895 Sq.kms (Coordinates: latitude 8° 25' and 8° 53' N and longitude 77° 10' and 77° 35' E.). KMTR comprises of 12 major forest types to sustain biodiversity including bat species. The annual precipitation in this area is 3,500 mm.

II. BACKGROUND STUDY

Many species of bats have highly developed ultrasonic bio-sonar capabilities, referred to as 'Echolocation', which they use to navigate and catch insects in total darkness. Echolocation [1], is a principle, also called as bio-sonar or biological sonar which is used by several kinds of animals including bats. Echo locating animals emit ultrasonic sounds (calls)- out to the environment and listen to the echoes of those calls that return from hitting the various objects near them. They use these echoes to locate and identify the objects. Echolocation is used for navigation and for foraging [2] (hunting, resting, feeding etc.) in various environments. Only insectivorous [3,4] 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.

Sound classification is recently evolving in the field of acoustic signal analysis [5]. An acoustic survey is one of the research methods of gathering information about the abundance of a species. Their presence is detected by using acoustic detectors. Acoustic surveys are carried out in a wide range of habitats to detect large number of species. Species identification is necessary to survey and monitor bat activity [6]. The echolocation calls of bats are recorded through bat detectors and are used for identification of species. The echolocation calls of bats (call structure and shape of calls)[7] differ from species to species, that is, the echolocation calls are species-specific[8]. This facilitates acoustic identification of bat species. However, call structures, shapes and frequencies within species can be extremely flexible and depend on factors including habitat, age, sex and the presence of conspecifics.[9,10]

Identification of bats from their calls can be split broadly into two paradigms: Qualitative and Quantitative. Qualitative methods involve researchers listening to calls [7], taking account of the echolocation call structure [8]. 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 [7]. 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. Quantitative methods are based on categorization of calls by clearly defined criteria, multivariate analysis if spectral and temporal parameters of calls and machine learning including Artificial Neural Networks. Multivariate and machine-learning methods can be repeated and they are also objective. Tests using calls of quality have posed some problems, but objective identification is possible.

Multivariate [13] discriminant functions have been used to identify calls of bats recorded in South–East England and Italy for habitat-use assessment [14]. A decision tree was used to classify zero-crossed echolocation call recordings from eight Australian species [15, 16]. Machine learning techniques which are used in automated (human) speech recognition [17-22] have been used to detect and classify calls from five North American bat species. These methods allow satisfactory identification of several species.

Support Vector Machines (SVM) [23, 24], Artificial Neural Networks (ANN) [25] and Synergetic Pattern Recognition [26] are the frequently used approaches to classify bats. Neural networks have 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 [7]; Greece [25]; Italy [27]; Mediterranean area[28]; UK [29]; Switzerland [26];). Therefore, they cannot be used to generate comparable classifications at a continental scale [10]. 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.

Walters et.al.[10] have said that a call library contains recordings of calls from a variety of species belonging to a region, using 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.

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 [10] and in other continents too. But there are not any for Indian bats. Hence in our research area, the Kalakad Mundanthurai Tiger Reserve [KMTR], we propose to build a classification scheme for the various bat species present in the KMTR region using Echolocation Calls.

III. METHODOLOGY

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. It is also possible to modify a portable Long Wave radio to be a bat detector by adjusting the tuning frequencies and replacing the ferrite rod aerial with a microphone and pre-amplifier. A bat detector is a device used to detect the presence of bats by converting their echolocation ultrasonic signals (as they are emitted by the bats), into 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 the inter-disciplinary science that deals with the study of sound waves including vibration, sound, ultrasound and infrasound. The Latin term ‘sonics’ is used as a synonym for ‘acoustics’. Frequencies above and below the audible range are called ‘ultrasonic’ and ‘infrasonic’ respectively.

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 audio classification.

A. *Perceptual, Spectrum and Cepstral Feature-based Bat Classification*

The presence of bats is detected by using bat detectors, by converting their echolocation ultrasonic signals to audible frequencies. From this audio signal the features are extracted. This signal is pre-emphasized with parameter 0.96 (8-bit ISDN μ-law encoding) and then divided into frames. The frames are of 256 samples (32ms) each, with sampling frequency of 8000 Hz and 25% (64 samples or 8ms) overlap in each of the two adjacent frames. Hamming-window is applied to a frame by wi = 0.54 – 0.46 * cos(2πi/ 256). If $\sum_{(i=1)}^{256}(w_i S_i)^2 < 400^2$ then, it is marked as a silent frame, where Si is the pre-emphasized signal magnitude at i and 4002 is an empirical threshold. Audio features are then extracted from each non-silent frame.

The frequencies and amplitudes of the frequencies of a signal can be calculated by Fourier analysis. To compute the discrete Fourier transform (DFT) and its inverse, an algorithm called a Fast Fourier transform (FFT) is applied. A Fourier transform converts time (or space) to frequency and vice versa; an FFT rapidly computes such transformations. As a result, fast Fourier transforms are widely used for many applications in engineering, science, and mathematics.

For each frame, FFT is applied. Nineteen different parameters along with call duration [Cdur] were extracted. Their definitions are given in the following, where the FFT [30] coefficients are computed from the frame.

Total Spectrum Power [24], Subband Powers, Brightness and Bandwidth of FFT coefficients are estimated. The pitch frequency feature is obtained using a simple pitch detection algorithm which is based on detecting the peak of the normalized auto-correlation function. The pitch frequency is returned if the peak value is above a threshold (T = 0.65, chosen empirically), or the frame is labelled as non-pitched otherwise. The call duration feature is measured by dividing the number of samples in the isolated call by the sample rate, after being isolated from the background signal.

Frequency at the start of the extracted call (kHz) was obtained by taking a 1024-point power spectrum of the first 256 μs of the call (resolution 3.9 kHz) and noting the frequency with most energy; the signal was zero padded to 1024 samples before the FFT was applied. This procedure was repeated for the centre and final 256 μs of the call to obtain the Frequency at half the duration of the call (kHz) and the Frequency at the end of the call. The Frequency with maximum energy (kHz) was obtained by applying a FFT to the entire isolated call. As calls varied greatly in length, and therefore number of samples, each call was first zero padded to increase its length to the nearest power of two before the FFT was applied. The resulting power spectrum was then reduced to 1024-samples using a moving average filter and the frequency at the maximum energy of the call measured. The next parameter estimated the rate of change (i.e. second order derivative) of the frequency- time course of each call (RoC, expressed at kHz/ms2). The frequency-time course was calculated by measuring the frequency with peak amplitude from successive power spectra taken throughout the call. Each power spectrum was calculated from a zero-padded 1024-point FFT of successive 128 μs portions of the call. Each successive power spectra overlapped the previous one by 80% (102.4 μs) giving a resolution in the frequency-domain of 1.6 kHz. The frequency with maximum amplitude of each power spectrum was used to mark out the frequency-time course of the call.

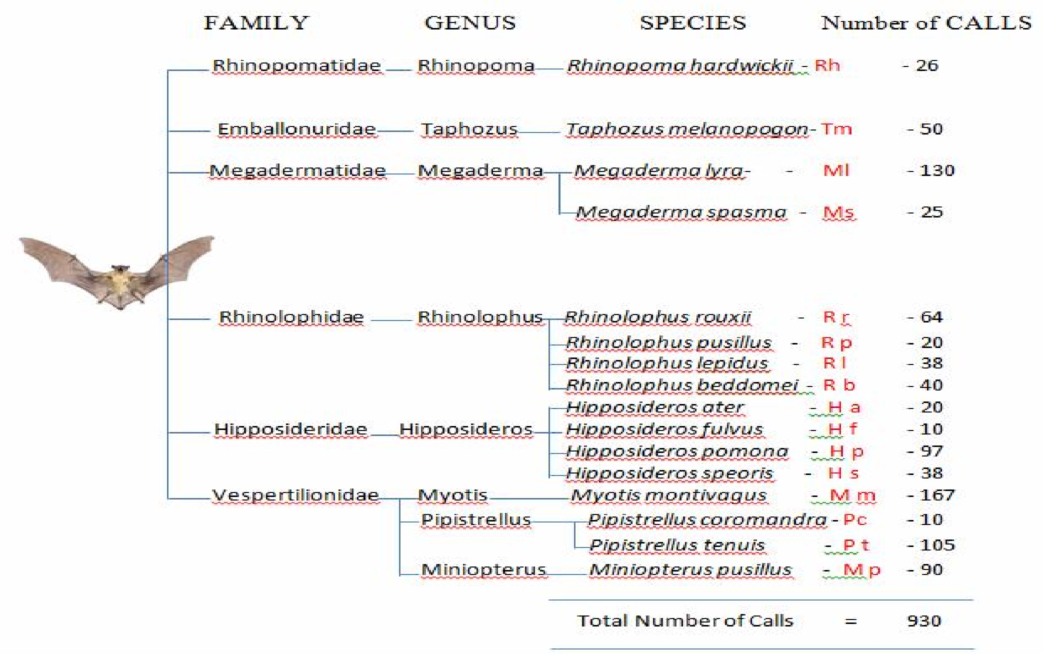
The next parameter is a standardised bandwidth measurement taken from a normalised version of the power spectrum calculated to measure frequency with maximum energy of the call. Standardised bandwidth was defined and measured as the bandwidth of the call at 80% of the maximum amplitude. A high bandwidth measurement denotes a relatively broad spread of energy across the echolocation call while a low value energy focused into a narrow range of frequencies. Four parameters are extracted to measure the distribution of energy across an echolocation call. Each call was subjected to a Hilbert transform and Multiplied by its conjugate; the output was normalised between zero and one. The resulting signal was separated into four quartiles, and the sum of each quartile's amplitude was divided by the sum of the signal's total amplitude. This gave the energy each quartile contained expressed as a proportion of the call's total energy. The next parameter, degree of frequency modulation is calculated by comparing the initial peak frequency, and the final peak frequency of the quarter.

The next type of feature is the MFCCs -*Mel-Frequency Cepstral Coefficients* [31]. From the FFT power coefficients, MFCCs are computed. A triangular bandpass filter bank is used to filter the power coefficients. The filter bank consists of K = 19 triangular filters. They have a constant mel-frequency interval, and covers the frequency range of 0Hz-4000Hz. Denoting the output of the filter bank by Sk (k = 1, 2, …., K), the MFCCs are calculated as, $c_n = \sqrt{\left(\frac{2}{k}\right)}\sum_{k=1}^{k}(\log Sk)$ cos[n (k-0.5) π / K] n = 1, 2, …., L, where L is the order of the cepstrum.

A 38+Cdur+2L -dimensional feature vector is formed when the means and standard deviations of the FFT and MFCC features are computed over the nonsilent frames, where 38 represents the means and standard deviations of all the FFT features, Cd represents the Call Duration and 2L represents that for the Cepstral coefficients[31]. The means and standard deviations of the L MFCCs are also calculated over the nonsilent frames, giving a 2L -dimensional cepstral feature vector. The k-nearest neighbor algorithm is amongst the simplest of all machine learning algorithms: an object is classified by a majority vote of its neighbors, with the object being assigned to the class most common amongst its k nearest neighbors (k is a positive integer, typically small). If k = 1, then the object is simply assigned to the class of that single nearest neighbor. In this approach, the k-NN classifier is used to classify the species.

IV. EXPERIMENTAL ANALYLSIS & RESULTS

The Megabats or the fruit-eating bats do not echolocate but the micro bats or the insect-eating bats use echolocation much. There are six families of insectivorous bats (microchiroptera)[3,4] which are found in the KMTR region. They are i) Rhinopomatidae ii) Emballonuridae iii) Megadermatidae iv) Rhinolophidae v) Hipposideridae vi) Vespertilionidae[37]. In the family Rhinopomatidae, one genus by name Rhinopoma is found. The name of the species found is *Rhinopoma hardwickii*. In the family Emballonuridae, one genus by name Taphozus is found. The name of the species found is *Taphozus melanopogon*. In the family Megadermatidae, one genus by name Megaderma is found. The two species found are *Megaderma lyra* and *Megaderma spasma*. In the family Rhinolophidae, one genus by name Rhinolophus is found. The four species found are *Rhinolophus rouxii*, *Rhinolophus pusillus*, *Rhinolophus lepidus* and *Rhinolophus beddomei*. In the family Hipposideridae, one genus by name Hipposideros is found. The four species found are *Hipposideros ater*, *Hipposideros pomona*, *Hipposideros fulvus* and *Hipposideros speoris*. In the family Vespertilionidae, three genuses namely Myotis, Pipistrellus and Miniopterus are found. In the genus Myotis, the species *Myotis montivagus* is found. In the genus, Pipistrellus, two species namely, *Pipistrellus coromandra* and *Pipistrellus tenuis* are found. In the genus Miniopterus, the species *Miniopterus pusillus* is found.



V. ANALYLSIS & METRICS

In this experiment the analysis metrics such as True Positive (TP), False Positive (FP), Sensitivity, Specificity and Accuracy were used to evaluate the performance of the classification schemes, Perceptual and Cepstral Feature-based Bat Classification [PCF] and Perceptual, Spectrum and Cepstral Feature-based Bat Classification [PSCF].

TABLE I

Perceptual, and Cepstral Feature-based Bat Classification						
	Bat Species	TP	FP	Sensitivity	Specificity	Accuracy
1	Rhinopoma hardwickii	9	2	69.23%	60%	66.66%
2	Taphozus melanopogon	23	1	63.33%	57.14%	62.16%
3	Megaderma lyra	65	2	61.11%	33.33%	59.37%
4	Megaderma spasma	10	2	76.92%	60%	55%
5	Rhinolophus rouxii	22	2	60%	50%	65%
6	Rhinolophus pusillus	8	1	80%	60%	60%
7	Rhinolophus Lepidus	18	2	65.21%	57.14%	63.33%
8	Rhinolophus beddomei	14	2	60%	50%	57.69%
9	Hipposideros ater	7	2	60%	60%	60%
10	Hipposideros fulvus	3	1	60%	66.66%	63.63%
11	Hipposideros pomona	40	3	64.91%	70%	65.67%
12	Hipposideros speoris	18	2	69.56%	50%	65.51%
13	Myotis montivagus	78	3	67.28%	60%	66.66%
14	Pipistrellus coromandra	4	1	60%	60%	60%
15	Pipistrellus tenuis	49	2	72.30%	70%	72%
16	Miniopterus pusillus	38	3	69.09%	63.09%	68.18%
Average Accuracy						63.632%

The above table shows the True Positive, False Positive, Sensitivity, Specificity and Accuracy calculated for each of the sixteen bat species under consideration, with the Approach1 namely, Perceptual and Cepstral Feature-based Bat Classification.

TABLE II

Perceptual, Spectrum and Cepstral Feature-based Bat Classification

	Bat Species	TP	FP	Sensitivity	Specificity	Accuracy
1	Rhinopoma hardwickii	10	1	76.92%	80%	77.77%
2	Taphozus melanopogon	23	1	76.66%	85.71%	78.37%
3	Megaderma lyra	65	2	72.22%	66.66%	71.87%
4	Megaderma spasma	10	2	76.92%	60%	72.22%
5	Rhinolophus rouxii	22	2	64.70%	66.66%	65%
6	Rhinolophus pusillus	8	1	80%	80%	80%
7	Rhinolophus Lepidus	18	2	78.260%	71.42%	76.66%
8	Rhinolophus beddomei	14	2	70%	66.66%	69.23%
9	Hipposideros ater	7	2	70%	60%	66.66%
10	Hipposideros fulvus	3	1	60%	83.33%	72.72%
11	Hipposideros pomona	40	3	70.17%	70%	70.14%
12	Hipposideros speoris	18	2	78.26%	66.66%	75.86%
13	Myotis montivagus	78	3	72.89%	70%	72.64%
14	Pipistrellus coromandra	4	1	80%	80%	80%
15	Pipistrellus tenuis	49	2	75.38%	80%	76%
16	Miniopterus pusillus	41	3	74.54%	72.72%	74.24%
					Average Accuracy	73.715%

The above table shows the True Positive, False Positive, Sensitivity, Specificity and Accuracy calculated for each of the sixteen bat species under consideration, with the Approach2 namely, Perceptual, Spectrum and Cepstral Feature-based Bat Classification.

TABLE III

COMPARISON OF THE ACCURACY OF PERCEPTUAL, AND CEPSTRAL FEATURE-BASED BAT CLASSIFICATION AND PERCEPTUAL, SPECTRUM AND CEPSTRAL FEATURE-BASED BAT CLASSIFICATION

	Average Accuracy
Perceptual, and Cepstral Feature-based Bat Classification	63.632%
Perceptual, Spectrum and Cepstral Feature-based Bat Classification	73.715%

PCF- Perceptual and Cepstral Feature-based Bat Classification.

PSCF- Perceptual, Spectrum and Cepstral Feature-based Bat Classification.

The above graph shows that for Species1, namely, Rhinopoma hardwickii, Approach1 outperforms Approach2 by 11.11% and for the remaining species 16.21%, 12.50%, 17.22%,0.00%, 20.00%, 13.33%, 11.54%, 6.66%, 9.09%, 4.47%, 10.35%, 5.98%, 20.00%, 4.00% and 6.06% respectively.

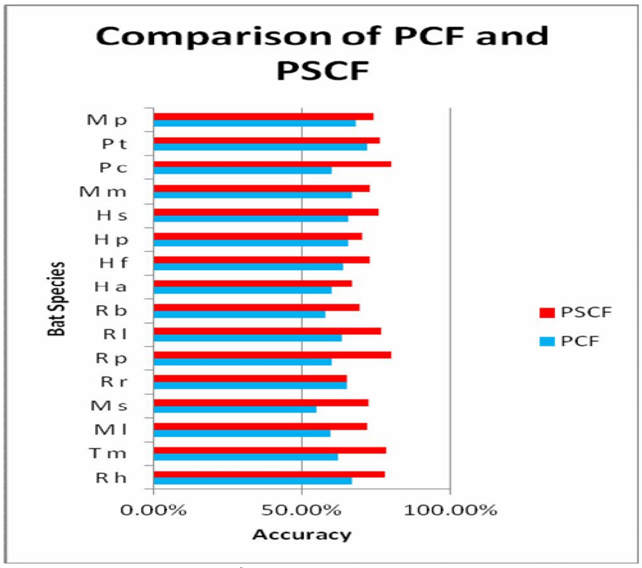


Fig. 1 A graph showing the comparison of accuracy with PCF and PSCF in all the sixteen species of bats

TABLE IV

	Bat Species	Notation
Species 1	Rhinopoma hardwickii	Rh
Species 2	Taphozus melanopogon	Tm
Species 3	Megaderma lyra	M l
Species 4	Megaderma spasma	M s
Species 5	Rhinolophus rouxii	Rr
Species 6	Rhinolophus pusillus	Rp
Species 7	Rhinolophus Lepidus	Rl
Species 8	Rhinolophus beddomei	Rb
Species 9	Hipposideros ater	Ha
Species 10	Hipposideros fulvus	Hf
Species 11	Hipposideros pomona	Hp
Species 12	Hipposideros speoris	Hs
Species 13	Myotis montivagus	Mm
Species 14	Pipistrellus coromandra	Pc
Species 15	Pipistrellus tenuis	Pt
Species 16	Miniopterus pusillus	Mp

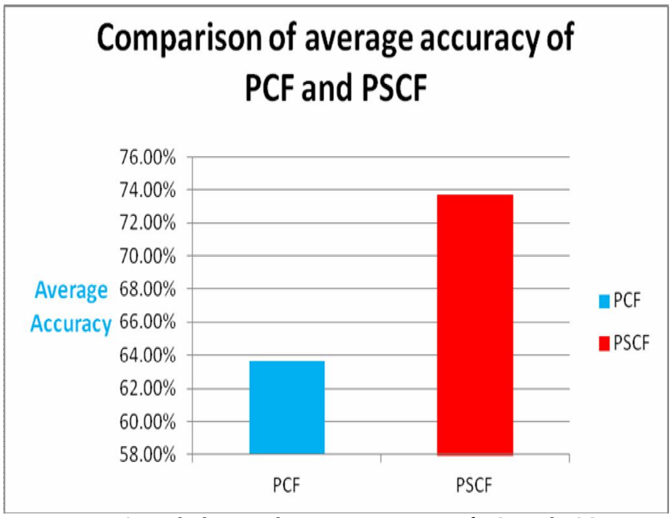


Fig. 2 A graph showing the average accuracy of PCF and PSCF

From the above graph it is clear that Perceptual and Cepstral Feature-based Bat Classification outperforms Perceptual, Spectrum and Cepstral Feature-based Bat Classification by 10.083%.

IV. CONCLUSIONS

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. In this paper, a classification scheme based on perceptual, spectrum and cepstral features was proposed for the classification of bats. It was compared with perceptual and cepstral feature-based classification scheme. It was found that perceptual, spectrum and cepstral feature-based bat classification scheme outperforms the perceptual and cepstral feature-based classification scheme and shows more accuracy. Acoustic identification of bats can be made use of to ensure objective identification of species.

ACKNOWLEDGMENT

The authors thank all anonymous reviewers for their thorough evaluation, constructive suggestions and recommendations for improving the content of the paper.

REFERENCES

[1] Jones G and Siemers, B M 2011. *The communicative potential of bat echolocation pulses.* Journal of Comparative Physiology A 197, 447-457 (2011)
[2] Schnitzler HU, Moss CF, Denzinger A 2003 *from spatial orientation to food acquisition in echolocating bats.* Trends EcolEvol 18:386-394
[3] Fenton M B and G P Bell 1981. *Recognition of species of insectivorous bats by their echolocation calls.* J.Mammal, 62: 233-243.
[4] Ochoa J, O'Farrell M J and Miller BW 2000. *Contribution of acoustic methods to the study of insectivorous bat diversity in protected areas from northern Venezuela.* ActaChiropt. 2: 171-183.
[5] Vaughan N, Jones G & Harris S 1997. *Habitat use by bats (Chiroptera) assessed by means of a broad-band acoustic method.* Journal of Applied Ecology1997, 34, 716-730
[6] Wickramasinghe L P, Harris S, Jones C and Vaughan N 2003. *Bat activity and species richness on organic and conventional farms: impact of agricultural intensification.* J. Appl. Ecol. 40: 984-993. doi: 10.1111/j.1365-2664.2003.00856.x.
[7] Murray, K. L., E. R. Britzke, and L. W. Robbins. 2001. *Variation in Search Phase Calls of Bats.* J. Mammalogy, 82:728-737.
[8] Betts B J 1998. *Effects of interindividual variation in echolocation calls on identification of big brown and silver-haired bats.* J. Wildl.Manag. 62: 1003-1010. doi: 10.2307/3802553
[9] Orbist M K 1995. *Flexible bat echolocation: the influence of individual, habitat and conspecifics on sonar signal design.* Behav. Ecol. Sociobiol. 36: 207-219. doi : 10.1007/s002650050142
[10] Walters C, Freeman R, Dietz C, Fenton B, Jones G, Maltby A et al. 2012. *A continental-scale tool for acoustic identification of European bats.* Journal of Applied Ecology 49, 1064–1074. http://dx.doi.org/10.1111/j.1365-2664.2012.02182.x
[11] Jennings N, Parsons S and Pocock MJO 2008. *Human vs machine: identification of bat species from their echolocation calls by humans and by artificial neural network.* Canadian Journal of Zoology 86, 371-377.
[12] Glendell M and Vaughan N 2002. *Foraging activity of bats in historic landscape parks in relation to habitat composition and park management.* Anim. Conserv. 5: 309-316.
[13] Vaughan N, Jones G & Harris S 1997. *Identification of British bat species by multivariate analysis of echolocation calls*. Bioacoustics, 7, 189-207.
[14] Vaughan N, Jones G and Harris S 1996. *Effects of sewage effluent on the activity of bats (Chiroptera: Vespertionidae) foraging along rivers.* Biol.Conserv. 78 : 337-343 doi:10.1016/S0006-3207(96)00009-2
[15] Herr A, Klomp N I and Atkinson J S 1997. *Identification of bat echolocation calls using a decision tree classification system* [online]. Complex. Int. 4. Available from http://journal-ci.csse.monash.edu.au/ci_louise/vol04/herr/batcall.html [accessed 1 April 2008]
[16] Herr A, Klomp N I, Atkinson J S 1997. *Identification of bat echolocation calls using a decision tree classification system.* Complexity International 1997, 4. http://www.complexity.org.au/ci/vol04/herr
[17] Skowronski M D and Harris J G 2006. *Acoustic detection and classification of microchiroptera using machine learning: lessons learned from automatic speech recognition.* J. Acoust.Soc.Am 119: 1817-1833. doi: 10.1121/1.2166948. PMID: 16583922
[18] Zhang Z, SchullerB 2012. *Semi-supervised learning helps in sound event classification.* IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) 2012.
[19] Rabiner L and JuangBH 1993. *Fundamentals of Speech Recognition.* Englewood Cliffs, NJ: Prentice-Hall, 1993.
[20] Ernawan F, Abu NA and SuryanaN 2012. *Efficient Discrete Tchebichef on Spectrum Analysis of Speech Recognition.* International Journal of Machine Learning and Computing 1(1), 1-6.
[21] Duzenli T and Ozkurt N 2011. *Discrete and Dual Tree Wavelet Features for Real-Time Speech/Music Discrimination.* ISRN Signal Processing Volume 2011 (2011), Article ID 269361, http://dx.doi.org/10.5402/2011/269361

[22] Adam TB, Salam MS and Gunawan TS 2013. *Wavelet Cepstral Coefficients for Isolated Speech Recognition.* TELKOMNIKA, Vol.11, No.5, May 2013, pp. 2731-2738.

[23] Redgwell, R D, Szewczak, J M, Jones G & Parsons S 2009. *Classification of echolocation calls from 14 species of bat by support vector machines and ensembles of neural networks.* Algorithms, 2, 907–924.

[24] Guo G and Li S Z 2003. *Content-based audio classification and retrieval by support vector machines. IEEE transactions on Neural Networks*, Vol.14, No.1, January 2003.

[25] Parsons S & Jones G 2000. *Acoustic identification of twelve species of echolocating bat by discriminant function analysis and artificial neural networks*. September 1, 2000. J ExpBiol 203, 2641-2656. PMID: 10934005

[26] Obrist M K, Boesch R &Fluckiger P F 2004. *Variability in echolocation call design of 26 Swiss bat species: consequences, limits and options for automated field identification with a synergetic pattern recognition approach*. Mammalia 68 (4): 307-322.

[27] Russo D & Jones G 2002. *Identification of twenty-two bat species (Mammalia: Chiroptera) from Italy by analysis of time-expanded recordings of echolocation calls*, Journal of Zoology, 258, 91-103.

[28] Russo D, Jones G 2003. *Use of foraging habits by bats (Mammalia: Chiroptera) in a Mediterranean area determined by acoustic surveys: conservation implications.* Ecography 2003, 26, 197-209.

[29] Walsh A L, Catto C M C, Hutson A M, Racey P A, *Richardson P and Langton S 2001. The UK's National Bat Monitoring Programme Final Report* 2001. Rep No CR018. Defra Publications, London.

[30] Katoh K, Misawa K, Kuma K and Miyata 2002. *MAFFT: a novel method for rapid multiple sequence alignment based in fast Fourier transform. Nucleic acids* Res.2002 July 15; 30(14): 3059-3066. PMCID: PMC135756

[31] Tzanetakis G, Essl G and Cook P 2000. *Audio Analysis using the Discrete Wavelet Transform. Organised sound,* Vol.4 (3), 2000.

[32] Chen L, Gunduz S, Ozsu MT, *Mixed type audio classification with support vector machine*. ICME, page 781-784. IEEE 2006.

[33] Wu JD and Liu CH 2008. *Investigation of engine fault diagnosis using discrete wavelet and neural network. Expert systems with applications*, Volume 35, Issue 3, October 2008, pages 1200-1213.

[34] Watson AB 1994. *Image Compression using the Discrete Cosine Transform*. Mathematical Journal, 4(1), 1994, p.81-88

[35] Ahlen I 1981. *Identification of Scandinavian bats by their sounds*. Rep. No. 6. Deparment of Wildlife Ecology, Swedish University of Agricultural Sciences, Uppsala.

[36] Weller T J, Seidman V M and Zabel C J 1998. *Assessment of foraging activity using Anabat II: a cautionary note*. Bat. Res. News, 39: 61-65.

[37] Kazial K A, Burnett S C and Masters W M 2001. *Individual and group variation in echolocation calls of big brown bats, Eptesicusfuscus (Chiroptera: Vespertilionidae).* J. Mammal. 82: 339-351. doi: 10.1644/1545-1542(2001)082<0339:IAGVIE>2.0.CO;2

[38] Jones G, Vaughan N and Parsons S 2000. *Acoustic identification of bats from directly sampled and time expanded recordings of vocalizations*. ActaChiropt. 2: 155-170.