IDENTIFICATION OF SELECTED FROGS ACOUSTICS SAMPLES USING WAVELET ENTROPY

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I hereby declare that the material in this thesis is my own except for quotations, excerpts, equations, summaries and references, which have been duly acknowledged.

9 January 2011

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ABSTRACT

IDENTIFICATION OF SELECTED FROGS ACOUSTICS SAMPLES USING WAVELET ENTROPY

Biodiversity is one of the major studies in bio-conservation, which enable to evaluate the quality of ecosystem in a specific area, especially for protected area. In order to monitor the quality of the ecosystem structure, a long term rapid diversity assessment is needed. In term of that, bioacoustics has been introduced as a beneficial method for local species richness estimation. However, this method is still in the infancy state and many improvements are needed for more practical purposes. This research is carried out to develop new bioacoustics species identification method using wavelet entropy with the improvement in the species identification accuracy. To evaluate the new identification system, a set of sound signals of nine frog species from Microhylidae family were collected. Ten syllables were segmented from each frog sound and extracted with the corresponding features which were carried out in this research, namely continuous wavelet entropy, discrete wavelet entropy and wavelet packet entropy as test samples. The test samples were then sent into the *k*-nearest neighbour (*k*-NN) classifier for species identification. Based on the test samples, this thesis work has proven that the wavelet packet entropy is the best method in the Tsallis entropy approach for species identification on bioacoustics signals.

ABSTRAK

Kepelbagaian biologi merupakan salah satu kajian utama dalam pemuliharaan biologi, di mana membolehkan untuk menilai kualiti ekosistem di tempat tertentu, terutamanya kepada kawasan yang terlindung, seperti hutan simpanan. Untuk pengawalan kualiti struktur ekosistem, kaedah penilaian secara masa panjang dan pantas adalah amat diperlukan. Dengan itu, kaedah bioakustik adalah diperkenalkan sebagai kaedah yang memanfaatkan untuk pengangaran kekayaan spesis tempatan. Akan tetapi, kaedah ini adalah masih di tahap yang tunas permulaan. Tujuan utama tesis ini adalah memperkenalkan kaedah baru untuk sistem pengecaman spesis bioakustik dengan meningkatkan ketepatan pengecaman. Kaedah yang dibangunkan dalam kajian ini adalah berdasarkan prinsip entropi wavelet. Isyarat bunyi daripada sembilan spesis katak keluarga Microhylidae dikumpul bertujuan untuk menilai kecekapan sistem pengecaman spesis baru dalam kajian ini. Sepuluh suku kata ('syllable') adalah ditemberengkan ('segmented') daripada setiap bunyi spesis katak tersebut dan seterusnya sifat-sifat suku kata adalah direntapkan ('extracted') dengan kaedah entropi wavelet seperti entropi wavelet berterusan, entropi wavelet diskrit dan entropi wavelet paket. Selepas kerentapan sifat ('feature extraction'), semua sampel kajian dikelaskan dengan menggunakan pengkelas k-NN bertujuan untuk mengenalpasti spesis katak. Daripada keputusan sampel kajian yang ditetapkan, adalah dibuktikan bahawa entropi wavelet paket merupakan kaedah yang terbaik dengan pendekatan entropi Tsallis dalam pengecaman spesis melalui isyarat bioakustik.

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LIST OF ABBREVIATIONS

ANFIS	Adaptive neuro-fuzzy interface system
ANN	Artificial neural network
ApEn	Approximation entropy
BGD	Boltzmann-Gibbs distribution
Bit	Binary digit
CJIS	Criminal Justice Information Services
CWT	Continuous wavelet transform
db4	Daubechies mother wavelet of order 4
DCT	Discrete cosine transform
DFA	Discriminant function analysis
DNA	Deoxyribonucleic acid
dpi	Dots per inch
DWE	Discrete wavelet entropy
DWT	Discrete wavelet transform
ECG	Electrocardiography
EEG	Electro-Encephalo-Gram
ERP	Endoscopic Retrograde Pancreatography
FBI	Federal Bureau of Investigation
FFT	Fast Fourier transform
FT	Fourier transform
GMM	Gaussian mixture model

HMM	Hidden Markov model
IWT	Inverse wavelet transform
JPEG	Joint Photographic Expert Group
***k*-NN**	*k*-nearest neighbour
LPC	Linear prediction coding
MFCC	Mel frequency cepstral coefficient
MRA	Multi-resolution analysis
OFDM	Orthogonal Frequency Division Multiplexing
PCA	Principal component analysis
PSCAD	Power Systems Computer Aided Design
EMTDC	Electromagnetic Transients including Direct Current
PD	Parkinson disease
PPM	Prediction by partial matching
QMF	Quadrature Mirror Filters
RE	Rényi entropy
RMS	Root mean square
SE	Shannon entropy
STFT	Short time Fourier transform
TE	Tsallis entropy
TF	Time-frequency
VDR	Volume dynamic ratio
WE	Wavelet entropy
WP	Wavelet packet

WPD	Wavelet packet decomposition
WPE	Wavelet packet entropy
WPEANFIS	WPE adaptive network based fuzzy inference system
WSE	Wavelet scale entropy
WT	Wavelet transform
WTE	Wavelet time entropy
WWW	World wide web

LIST OF SYMBOLS

English letters

a	Scale parameter in continuous wavelet transform
A	Approximation coefficients of wavelet transform
b	Time parameter in continuous wavelet transform
C	Coefficient of wavelet transform
d	Euclidean distance
D	Detail coefficients of wavelet transform
E	Energy
E_j	Energy of wavelet transform respect to corresponding scale parameter j
E_T	Total energy of wavelet transform
g	High pass filter
h	Low pass filter
H	Shannon entropy
i	Number of category
I	Message space
j	Transformation of scale parameter a
k	Discrete time
k_B	Boltzmann's constant
K	Number of nearest neighbour used in *k*-NN classifier
l	Maximum number of attribute
L	Filter length

n	Number of symbols
N	Total number of symbols
N_0	Number of samples in one period of time
N_c	Number of syllables which correctly recognized
N_T	Total number of test syllables
p	Probability
p_j	Relative wavelet energy by scale parameter j
P_k	Magnitude of the spectrum of bin number k
q	Heat
R_α	Rényi entropy of order α
S	Entropy in mechanical statistic
t	Continuous time
T_0	Period of time
T_α	Tsallis entropy of order α
u	Attribute instance with unknown classification
v	Attribute instance with known classification
$x(k)$	Discrete time signal
$x(t)$	Continuous time signal
x	Discrete random variable
$y(t)$	Noise signal

Greek letters

α	Parameter of entropy
β	Base of logarithm
ς	Conventional constant
$\square$	Uniform distribution
$\varepsilon(\,)$	Expected value function
ℓ	Complex number
λ	Decomposition level
η	Range of attributes
$\sigma\ (t)$	Square-integrable function
$\psi(k)$	Wavelet basis or mother wavelet
$\Theta(\,)$	Information content or self-information
ϕ	Number of microstates consistent with the given macrostate

Special symbols

$\Re$	Set of real numbers
$\mathring{a}$	Amplitude of signal
$L^2(\Re)$	Space of measurable

CHAPTER 1

INTRODUCTION

1.1 Research Background

Nothing would work in the absence of communication. Flowers must communicate with bees in order for pollination to be successful. Male songbirds must communicate with females if they are to mate and rear young. Lions on a cooperative hunt must communicate with each other about how they will attack their prey. For natural communication system, such as those observed in the plant and animal kingdoms, constraints can be seen at several levels including neurobiological, physiological and psychological. These constraints are important, for they determine the relative success of the organism in responding to socio-ecologically relevant stimuli in the environment. For all living organisms including humans, communication provides a vehicle for conveying information and for expressing to others what has been perceived. But organisms differ with regard to what they can convey and what they perceive. Consequently, there is a diversity of communication system in the natural world (Hauser, 1996). Because of that, the study of bioacoustics has become the interest of many researchers. Table 1.1 shows a list of definitions of communication from researchers in sociobiology, behavioural ecology, sensory ecology, neuropsychology, cognitive psychology, and linguistics – disciplines, where the concept of 'information' and 'signal' form integral components of most definitions of communication. Both concepts are associated with long lists of operation definitions. Thus information is a feature of an interaction between sender and perceiver. It is believed that, signal carries certain kinds of information content, which can be manipulated by the sender and differentially acted upon by the perceiver. Signals have been designed to serve particular functions and the functions they serve must be evaluated in light of both production and perception constraints.

Table 1.1: Some definitions of communication: A sampler (Hauser, 1996)

Authors (discipline)	**Definition**
Wilson (Sosiobiology)	"Communication occurs when the action of or cue given by one organism is perceived by and thus alters the probability pattern of behaviour in another organism in a fashion adaptive to either one or both of the participants".
Hailman (Ethology)	"Communication is the transfer of information via signals sent in a channel between a sender and a receiver. The occurrence of communication is recognised by a difference in the behaviour of the reputed receiver in two situations that differ only in the presence or absence of the reputed signal.... the effect of a signal may be to prevent a change in the receiver's output, or to maintain a specific internal behavioural state of readiness"
Dusenbery (Sensory ecology)	"The term 'true communication' is restricted to cases in which the transmitting organism engages in behaviour that is adaptive principally because it generates a signal and the interaction mediated by the signal is adaptive to the receiving organism as well"
Krebs and Davies (Behavioral ecology)	"The process in which actors use specially designed signals or displays to modify the behaviour of reactors"
Kimura (Neuropsychology)	"The term is used here in a narrower sense, to refer to the behaviours by which one member of a species conveys information to another member of the species"
Johnson-Laird (Cognitive psychology)	"Communication is a matter of causal influence... the communicator [must] construct an internal representation of the external world, and then... carry out some symbolic behaviour that conveys the content of that representation. The recipient must first perceive the symbolic behaviour, i.e. construct its internal representation of the state that it

	signifies. This final step depends on access to the arbitrary conventions governing the interpretation of the symbolic behaviour".
Lindblom (Linguistics)	"Human communication... includes forms of verbal communication such as speech, written language and sign language. It comprises nonverbal modes that do not invoke language proper, but that nevertheless constitute extremely important aspects of how we communicate. As we interact, we make various gestures – some vocal and audible, others nonvocal like patterns of eye contact and movements of the face and the body. Whether intentional or not, these behaviours carry a great deal of communicative significance".

One of the major tasks when analyzing animal sounds is the measurement of acoustically relevant features. There are many features which have been used in the bioacoustics analysis and classifications studies, where majority of these features are extracted manually (by hand) from spectrogram plots (Clemins and Johnson, 2006). Placer and Slovodchikoff (2004) have pointed out that, since the 1950s, animal vocalizations have been analyzed in the form of either sonograms or patterns of amplitude changes. Sonograms have been a popular choice for analysis, because sonograms display all of the constituent frequencies in a sound wave, and the resulting pattern can be easily visualized. In the earlier studies, investigators used to compare the pattern of sonograms and amplitude changes by eyes and searching for differences. Unfortunately, manual acoustic identification of species is very time consuming and analysis time can be as much as ten times longer than the recording (Chesmore, 2004). In order to speed up the process and likely to lead to the development of continuous real-time monitoring of biodiversity, the development of automated identification systems is needed.

Species identification using electronic instruments is defined as an application of general pattern recognition in which an unknown (specimen) is placed into one of a number of possible classes depending on features extracted from measurements on the species (Chesmore, 2004). One of the most difficult aspects of performing research in bioacoustics species recognition by machine is its interdisciplinary nature, and the tendency of most researchers to apply a monolithic approach to individual problems.

Generally, the development of automated bioacoustics recognition studies can be viewed from three aspects, which are: (1) the feature extraction, (2) the classification method and (3) the animal species.

Features used in sound recognition applications are usually chosen such that they represent some meaningful characteristics (Huang *et al.,* 2009). Selection of actual features used in recognition is a critical part for the recognition system. In term of bioacoustics recognition system, there are a lot of features which have already been discovered in the literatures. These features are introduced in the literatures are generally inspired from the work of speech recognition studies. These features normally can be categorized into two groups, time domain and frequency domain. Time domain approach for signal processing may include features such as frame energy, silence ratio, volume root mean square (RMS), volume dynamic ratio (VDR), total energy and zero-crossing ratio. Fourier transform based power spectrum, wavelet transform and linear prediction coding (LPC) coefficients are examples of methods used to extract relevant frequency (or time-frequency) contents for frequency (or time-frequency) domain techniques. The selection of the classification tool can also be seen as an important step to solve the pattern recognition problem. In term of bioacoustics classification, since there are not many studies in this field, only several pattern recognition methods can be found in the literatures, such as artificial neural networks (ANN) (Chesmore, 2001), data mining techniques, template matching method, *k*-nearest neighbour (*k*-NN) (Huang *et al.*, 2009), fuzzy-*k*-nearest neighbour (Dietrich *et al.*, 2003) and hidden Markov model (HMM) (Milone *et al.*, 2009). Again, these classifiers which are introduced in the literatures for bioacoustics identification are also influenced a lot by speech recognition methods (Rabiner and Juang, 1993). It is found that, similar to classification tools, there are only several animals which are being studied for bioacoustics classification. The majority of the studies on bioacoustics for species identification which can be found in literatures are mainly focused on some animal species, such as birds (Chesmore, 2001), frog (Huang *et al*, 2009), insects (Chesmore, 2004), whales (Clemins and Johnson, 2006), dolphin (Houser *et al.*, 1999) and bats (Vaughan *et al.*, 1996).

1.2 Research Objectives

This study is carried out to:

1. develop a bioacoustics species identification algorithm on selected frogs acoustics signal with the improvement in the identification accuracy by using wavelet entropy approach.
2. investigate several wavelet entropy properties using continuous wavelet transform (CWT), discrete wavelet transform (DWT) and wavelet packet (WP) based on Shannon, Rényi and Tsallis as a feature to characterize a bioacoustics signal.

1.3 Contribution of the Thesis

As mentioned earlier in this thesis, the development of bioacoustics species identification system helps in species identification, identification of individuals within a species and detection of the presence of animals. In other words, this system provides an opportunity to detect the appearance of new species in specific area and also the migration of certain animal species.

Furthermore, it is believed that the bioacoustics species identification system can be used to improve the quality of ecosystem monitoring system with the properties of long term, long distance, low cost and rapid diversity assessment and without invasion to the protected area during the activity of monitoring.

REFERENCES

Adam, O., Lopatka, M., Laplanche, C. and Motsch, J.-F. 2005. Sperm Whale Signal Analysis: Comparison using the AutoRegressive model and the Wavelet Transform. *International Journal of Information Technology*, **3**(1):1-8.

Alexander B.F. and Doyne F.J. 2008. The Physics of Information. Handbook of the Philosophy of Science. *In Vol. 8: Philosophy of Information*. United Kingdom: Elsevier B.V.

Avci, D. 2009. An expert system for speaker identification using adaptive wavelet sure entropy. *Expert Systems with Applications*. **35**:6295 – 6300.

Avci, E. 2008. Comparison of Wavelet Families for Texture Classification by Using Wavelet Packet Entropy Adaptive Network Based Fuzzy Inference System. *Applied Soft Computing*, **8**(1):225–231.

Avery, J. 2003. *Information Theory and Evolution*. World Scientific.

Bauk, S. 1991. *Asas-Asas Fizik Statistik dan Terma*. Kuala Lumpur: Dewan Bahasa dan Pustaka.

Beck, C. 2009. Generalized Information and Entropy Measures in Physics. *Contemporary Physics*, **50**(4):495 – 510.

Bercher, J.-F. 2008. On Some Entropy Functionals Derived from Rényi Information Divergence. *Information Sciences*, **178**:2489–2506.

Bezerianos, A., Tong, S., Zhu, Y. and Thakor, N. 2001. *Nonadditive Information Theory for the Analysis of Brain Rhythms*. Engineering in Medicine and Biology Society, 2001. Proceedings of the 23rd Annual International Conference of the IEEE, **2**:1923–1925.

Burrus, C.S., Gopinath, R.A. and Guo, H.T. 1998. *Introduction to Wavelet and Wavelet Transforms*. New Jersey: Prentice Hall.

Campbell, L. and Garnett, W. 2001. *The Life of James Clerk Maxwell: With Selections from His Correspondence and Occasional Writings*. London: Adamant Media Corporation.

Chesmore, E.D. 2001. Application of time domain signal coding and artificial neural networks to passive acoustical identification of animals. *Applied Acoustics*, **62**:1359 – 1374.

Chesmore, E.D. 2004. Automated bioacoustic identification of species. *An. Acad. Bras. Ciênc*, **76**(2): 435 – 440.

Chiou, R.C.H., Alice, M., Ferreira, G.V., Silva, C.T. and Kaufman, A.E. 1998. *Wavelet and Entropy Analysis Combination to Evaluate Diffusion and Correlation Behaviours.* SIBGRAPI 97 – X Brazilian Symposium of Computer Graphic and Image Processing, Campos de Jordao, SP, Brazil, 13 – 16 October 1997, IEEE Computer Society, 119 - 125.

Clemins, P.J. and Johnson, M.T. 2006. J. Generalized perceptual linear prediction features for animal vocalization analysis. *Acoustical Society of America*, **120**(1):527–534.

Cohen, A. and Ryan, R.D. 1995. *Applied Mathematics and Mathematical Computation 11: Wavelets and Multiscale Signal Processing.* London: Chapman & Hall.

Cover, T M. and Thomas, J.A. 2006. *Elements of Information Theory.* (2nd edition). New Jersey: John Wiley & Sons, Inc.

Crowe, J.A., Gibson, N.M., Woolfson, M.S. and Somekh, M.G. 1992. Wavelet Transform as a Potential Tool for ECG Analysis and Compression. *J. Biomed. Eng.* **14**(3):268–272.

Dhubkarya, D.C. and Dubey, S. 2009. High Quality Audio Coding at Low Bit Rate Using Wavelet And Wavelet Packet Transform. Journal of Theoretical and Applied Information Technology. 194-200.

Dietrich, C., Palm, G., and Schwenker, F. 2003. Decision templates for the classification of bioacoustic time series. *Information Fusion*, **4**:101–109.

Doyle, L.R., McCowan, B., Hanser, S.F., Chyba, C., Bucci, T., and Blue, J.E. 2008. Applicability of Information Theory to the Quantification of Responses to Anthropogenic Noise by Southeast Alaskan Humpback Whales. *Entropy*, **10**:33-46.

Emmert-Sterib, F., Dehmer, M. 2009. *Information Theory and Statistical Learning.* New York: Springer Science + Business Media, LLC.

Giannakakis, G.A., Tsiaparas, N.N., Xenikou, M-.F.S., Papageorgious, C. and Nikita, K.S. 2008. Wavelet Entropy Differentiations of Event Related Potentials in Dyslexia. In the proceedings of 8th IEEE international Conference on Bioinformatics and Bioengineering, Athens, Greece, 8-10 October 2008.

Goswami, J.C. and Chan, A.K. 1999. *Fundamentals of Wavelets: Theory, Algorithms, and Applications*. Canada: John Wiley & Sons, INC.

Gray, R.M. 1990. *Entropy and Information Theory*. New York: Springer-Verlag.

Hadzibeganovic, T. and Cannasc. S.A. 2009. A Tsallis' statistics based neural network model for novel word learning. *Physica A*, **388**:732-746.

Han, Y., Ma, Z.H., Zhou, P. and Liu, Z.C. 2009. Analysis of Parkinson Gait Based on Wavelet Packet Entropy. World Congress on Medical Physics and Biomedical Engineering. SpringerLink, September 7 – 12, 2009, Munich, Germany. 452–455.

Hanser, S.F., McCowan, B., Doyle, L. 2000. Information Theory as a Comparative Measure of Animal Communication Comlexity. *ASP Conference Series*, **213**:613–617.

Harremoës, P. and Topsøe, F. 2008. The Quantitative Theory of Information. Handbook of the Philosophy of Science. *In Vol. 8: Philosophy of Information*. United Kingdom: Elsevier B.V.

Hauser, M.D. 1996. *The Evolution of Communication*. London: The MIT Press.

He, Z.Y., Chen, X.Q. and Qian, Q.Q. 2005. A Study of Wavelet Entropy Measure Definition and Its Application for Fault Feature Pick-Up and Classification. *Journal of Electronics, Science Press, co-published with Springer-Verlag GmbH*, **24**(5):628–634.

Houser, D.S., Helweg, D.A. and Moore, P.W. 1999. Classification of Dolphin Echolocation Clicks by Energy and Frequency Distribution. *Journal of Acoustics Society of America*. **106**:1579 – 1585.

Huang, C.J., Yang, Y.J., Yang, D.X. and Chen, Y.J. 2009. Frog classification using machine learning techniques. *Expert System Application*. **36**:3737–3743.

Hubbard, B.B. 1996. *The World According to Wavelets: The story of a Mathematical Technique in the Making*. United States: Peter, A.K. Ltd.

Kuncheva, L.I. 2004. *Combining Pattern Classifiers: Methods and Algorithm*. New Jersey: John Wiley & Sons, Inc.

Learned, R.E. 1992. *Wavelet Packet Based Transient Signal Classification*. Master thesis. Massachusetts Institute of Technology.

Li, s., Wang, J.Q., Liu, T. and Jing, X.J. 2009. Wavelet Packet Entropy for Millimeter Wave Conducted Speech Enhancement. *Noise Control Engineering Journal*, **57**(5):543–550.

Mallat, S. 2009. *A Wavelet Tour of Signal Processing: The Sparse Way*. (3rd edition). United State: Academic Press, Elsevier.

Maszczyk, T. and Duch, W. Comparison of Shannon, Renyi and Tsallis Entropy used in Decision Trees. 2008. *Springer Berlin / Heidelberg*, 643-651.

Milone, D.H., Rufiner, H.L., Galli, J.R., Laca, E.A. and Cangiano, C.A. 2009. Computational method for segmentation and classification of ingestive sounds in sheep. *Computers and Electronics in Agriculture*, **65**:228–237.

Munoz, A., Ertlé, R. and Unser, M. 2002. Continuous Wavelet Transform with Arbitrary Scales and *O*(*N*) Complexity. *Signal Processing*, 749 – 757.

Ocak, H. 2006. Automatic detection of epileptic seizures in EEG using discrete wavelet transform and approximate entropy. *Expert Systems with Application*, **36**:2027–2036.

Oppenheim, A.V. and Schafer, R.W. 1975.*Digital Signal Processing*. Prentice Hall.

Peterson, M.R., Doom, T.E. and Raymer, M.L. 2005. GA-facilitated KNN classifier optimization with varying similarity measures. *The 2005 IEEE Congress on Evolutionary Computation*. **3**:2514 – 2521.

Petz, D. 2001. Entropy, von Neumann and the von Neumann Entropy. *John von Neumann and the Foundations of Quantum Physics, eds*. 1-10.

Placer, J. and Slobodchikoff, C.N. 2004. A Method for Identifying Sounds used in the Classification of Alarm Calls. *Behavioural Processes*, **67**: 87 – 98.

Plastino, A. 2004. Why Tsallis` Statistics? *Physica A*, **344**:608–613.

Rabiner, L. and Juang, B-.H. 1993. *Fundamentals of Speech Recognition*. New Jersey: Prince Hall.

Rosso, O.A. Blanco, S. Yordanova, J. Kolev, V. Figliola, A. Schurmann, M. and Bas-ar, E. 2001. Wavelet entropy: a new tool for analysis of short duration brain electrical signals. *J. Neurosci. Method*, **105**:65–75.

Ruch, D.K., and van Fleet, P.J. 2009. *Wavelet Theory: An Elementary Approach with Applications*. United State: Jon Wiley & Sons, Inc.

Rufiner, H.L., Torres, M.E., Gamero, L. and Milone, D.H. 2004. Introducing Complexity Measures in Nonlinear Physiological Signals: Application to Robust Speech Recognition. *Physica A*. **332**:496–508.

Safty, S.El., El-Zonkoly, A. 2009. Applying Wavelet Entropy Principle in Fault Classification. *International Journal of Electrical Power & Energy Systems*, **31**(10):604–607.

Selin, A., Turunen, J. and Tanttu, J.T. 2007. Wavelet in recognition of bird sounds. *EURASIP Journal on Advances in Signal Processing*, **2007**:ID 51806.

Sethna, J.P. 2006. Statistical Mechanics: Entropy, Order Parameters and Complexity. New York: Oxford University Press.

Shannon, C.E. 1948. A Mathematical Theory of Communication. *The Bell System Technical Journal*. **27**:379–423.

Sueur, J., Pavoine, S., Hamerlynck, O. and Duvail, S. 2008. Rapid Acoustic Survey for Biodiversity Appraisal. *PLos ONE*, **3** (12):e4065.

Sun, L., Chang, G.L. and Tang, H.R. 2006. *Wavelet Packet Entropy in the Analysis of EEG signals*. ICSP 2006 Proceedings.

Suzuki, R., Buck, J.R., Tyack, P.L. 2006. Information entropy of Humpback Whale Songs. *Acoustical Society of America*, 1849 – 1866.

Tsallis, C. 2009. Nonadditive Entropy and Nonextensive Statistical Mechanics – An Overview After 20 Years. *Brazilian Journal of Physics*, **39**(2A):337–356.

Ullmann, J.R. 1973. *Pattern Recognition Techniques*. Crane, New York: Russak & Company, Inc.

Van der Lubbe, Jan C.A. 2002. *Information Theory*. United Kingdom: Cambridge University Press.

Vaughan, N. Jones, G. Harris, S. 1996. Identification of British bat species by multivariate analysis of echolocation call parameters. *Journal of Bioacoustics*, **7**:189–207.

Vetterli, M. and Kovačević, J. 1995. *Wavelets and Subband Coding*. New Jersey: Prentice Hall.

Krishnan V., Babu V.R., Anto P., 2009. Features of Wavelet Packet Decomposition and Discrete Wavelet Transform for Malayalam Speech Recognition. *International Journal of Recent Trends in Engineering*, **1**(2).

Walker, J.S. 2008. *A Primer on Wavelets and Their Scientific Applications*. (2nd edition). United State: Chapman & Hall/CRC.

Webb, A.R. 2002.*Statistical Pattern Recognition*. (2nd edition). Malvern, UK: John Wiley & Sons, LTD.

Wu, J-.D. and Lin, B-.F. 2009. Speaker identification using discrete wavelet packet transform technique with irregular decomposition. *Expert Systems with Applications*. **36**:3136–3143.

Yildiz, A., Akin, M., Poyraz, M. and Kirbas, G. 2009. Application of adaptive neuro-fuzzy inference system for vigilance level estimation by using wavelet-entropy feature extraction. *Expert System with Application*, **36**:7390–7399.

Young, H.D. and Freedman, R.A. 2000. *University Physics with Modern Physics*. 10th edition. United States: Addison-Wesley Publishing Company.

Young, R.K. 1993. *Wavelet Theory and Its Applications*. London: Kluwer Academic Publishers.

Yulmetyev, R.M. Emelyanova, N.A. and Gafarov, F.M. 2004. Dynamical Shannon entropy and information Tsallis entropy in complex systems. *Physica A*, **341**:649–676.

Zunino, L., Pérez, D.G., Garavaglia, M. and Rosso, O.A. 2007. Wavelet Entropy of Stochastic Processes. *Physica A*, **379**:503–512.