Nonlinear Processing of Fish Sounds Acquired Through Passive Acoustic Technique

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1. Abstract

Many naturally occurring signals are found to be multifractal in nature (example, human heart beats), here we try to examine the multifractality of fish sounds. Terapon, Toad, Barred Grunt and Sciaenidae; This study was based on these fish species. Species based clustering was observed using features extracted through multi-fractal detrended fluctuation analysis (MFDFA). The highest and the lowest degree of multifractality was observed in Sciaenidae and Terapon respectively. The type of multifractality was identified by using shuffling. Also the singularity spectrum obtained was analysed to obtain three important features namely, the spectrum width, the range and the asymmetry parameter (B).

2. Nonlinear phenomena

The framework of nonlinear phenomena (NLP) from the physics discipline is now being used to explain bioacoustic observations including species characterization. The NLP is rooted in the intrinsic nonlinear oscillations of the acoustic signal generated during the sound production. Four major types of NLP have been documented, as can be gleaned from different seminal scientific literature.

(1) Frequency jump: a signal spectrum comprises of a fundamental frequency f0, and the frequency jump represents a break in the f0 with abrupt and discontinuous increase or decrease in the vibration rate. (2) Subharmonics: the additional intermediate spectral components that appear in the harmonic stack, typically at integer fractions of the fundamental frequency f0 (i.e., f0=2, f0=3). (3) Biphonation: the simultaneous occurrence of two independent fundamental frequencies. (4) Deterministic chaos: a broadband frequency segment in the signal spectrum, with energy at many different frequencies. NLP are common in human and in animal vocalizations, particularly among: Mammalians, common chimpanzee, rhesus macaque, meerkat, Corsican red deer, dog, red wolf, whale, and manatee. Aves cockatoo, magpie, zebra finch, and northern mockingbird. Reptiles, pisces, amphibians, and insects.

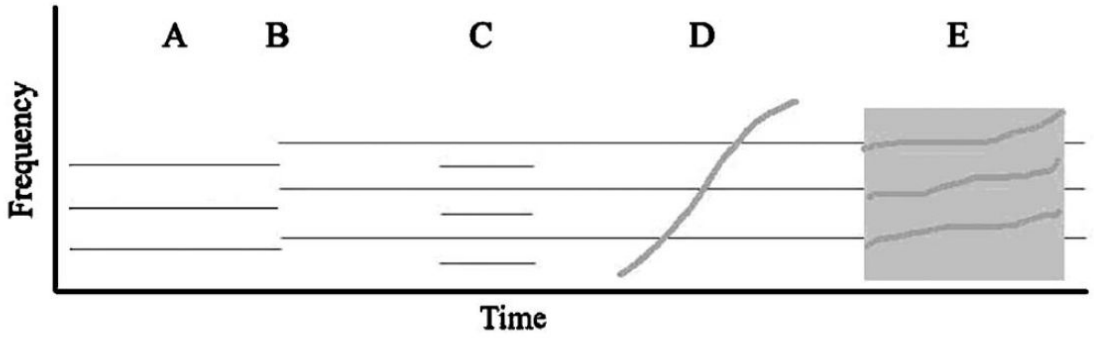


FIG. 1. Schematic narrowband spectrograms illustrating stable limit cycle (a), frequency jump (b), subharmonics (c), biphonation (d) and deterministic chaos (E) (modified after Fig. 1 from Riede *et al.*, 2004).

3. Preprocessing

3.1. Calibration

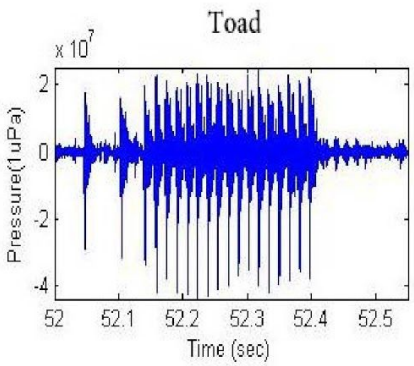
The data was collected by deploying SM2 M+ hydrophones in Grand Island, Mandovi, etc. This has a sensitivity of -165 dB/uPas hence, the data should be appropriately amplitude adjusted. These samples were collected periodically (15-minute gaps) through a number of days. All species of excluding Barred Grunt were recorded at 44.1KHz while Barred Grunt was recorded at 16Khz.

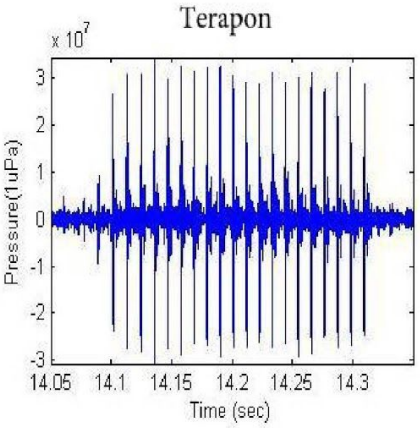
3.2. Filter

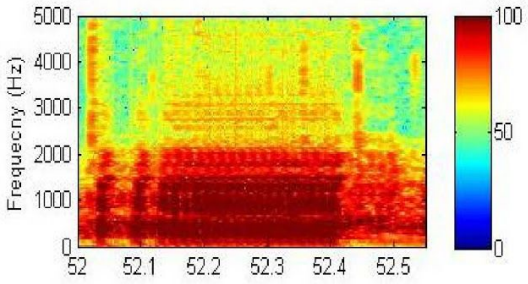
All fish sounds lie in a frequency band of 100Hz to 2KHz to avoid other interferences in the analysis a Butterworth bandpass filter of 6th order was applied.

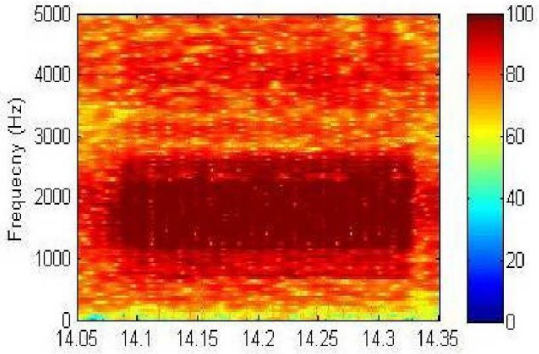
3.3. Segmentation

For each species 20 best (noise free) samples were selected with careful observation of their oscillograms, spectrograms and power spectral densities.


Toad
x 10^7
Pressure(1uPa)
Time (sec)


Terapon
x 10^7
Pressure(1uPa)
Time (sec)


Frequecny (Hz)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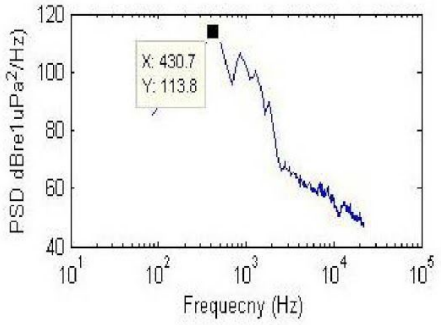
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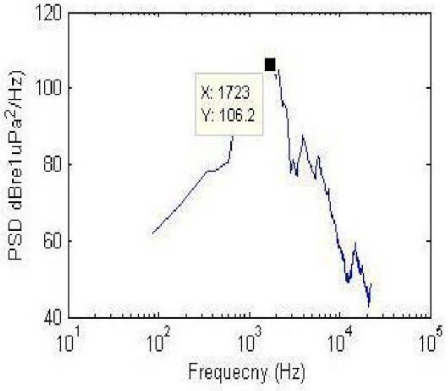
Y: 113.8
PSD dBre1uPa²/Hz)
Frequecny (Hz)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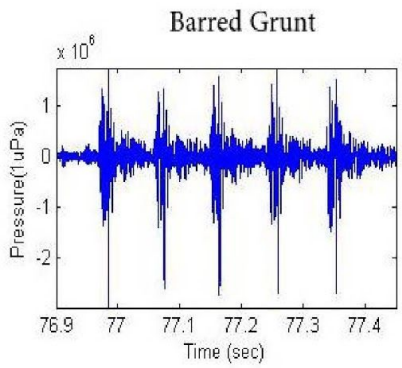
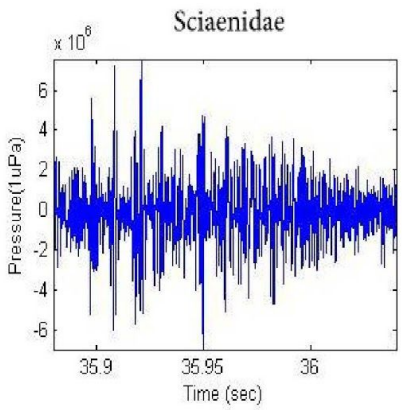
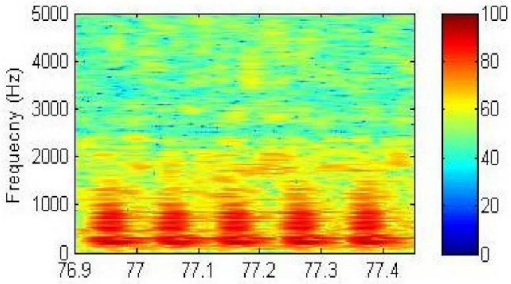
Y: 106.2
PSD dBre1uPa²/Hz)
Frequecny (Hz)


Barred Grunt
x 10^6
Pressure(1uPa)
Time (sec)


Sciaenidae
x 10^6
Pressure(1uPa)
Time (sec)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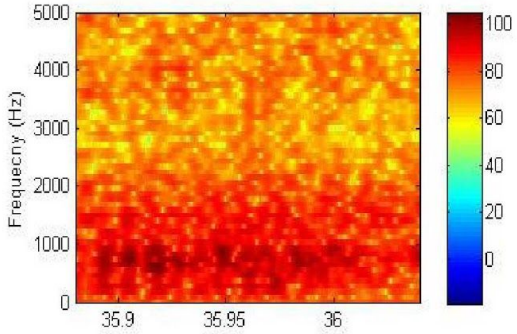
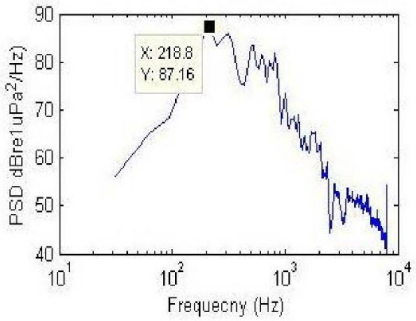
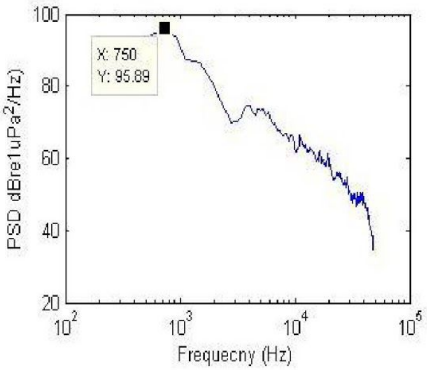

Frequecny (Hz)


X: 218.8
Y: 87.16
PSD dBre1uPa²/Hz)
Frequecny (Hz)


X: 750
Y: 95.89
PSD dBre1uPa²/Hz)
Frequecny (Hz)

4. MFDFA

4.1. Brief overview of MFDA

In recent years the detrended fluctuation analysis (DFA) method has become a widely-used technique for the determination of (mono-) fractal scaling properties and the detection of long-range correlations in noisy, nonstationary time series. It has successfully been applied to diverse fields such as DNA sequences, heart rate dynamics, neuron spiking, human gait, long-time weather records, cloud structure, geology, ethnology, economics time series, and solid state physics. One reason to employ the DFA method is to avoid spurious detection of correlations that are artifacts of nonstationarities in the time series. Many records do not exhibit a simple monofractal scaling behavior, which can be accounted for by a single scaling exponent. In some cases, there exist crossover (time-) scales s× separating regimes with different scaling exponents, e. g. long-range correlations on small scales s ≪ s× and another type of correlations or uncorrelated behavior on larger scales s ≫ s×. In other cases, the scaling behavior is more complicated, and different scaling exponents are required for different parts of the series. This occurs, e. g., when the scaling behavior in the first half of the series differs from the scaling behavior in the second half. In even more complicated cases, such different scaling behavior can be observed for many interwoven fractal subsets of the time series. In this case a multitude of scaling exponents is required for a full description of the scaling behavior, and a multifractal analysis must be applied. The simplest type of multifractal analysis is based upon the standard partition function multifractal formalism, which has been developed for the multifractal characterization of normalized, stationary measures. Unfortunately, this standard formalism does not give correct results for nonstationary time series that are affected by trends or that cannot be normalized. Thus, in the early 1990s an improved multifractal formalism has been developed, the wavelet transform modulus maxima (WTMM) method, which is based on wavelet analysis and involves tracing the maxima lines in the continuous wavelet transform over all scales.

The structural characteristics of biomedical signals are often visually apparent, but not captured by conventional measures like the average amplitude of the signal. Biomedical signals from a wide range of physiological phenomena possess a scale invariant structure. A biomedical signal has a scale invariant structure when the structure repeats itself on subintervals of the signal. Formally, the biomedical signal X(t) are scale invariant when X(ct) = c HX(t). Fractal analyses estimates the power law exponent, H, that defines the particular kind of scale invariant structure of the biomedical signal. Fractal analyses are frequently employed in biomedical signal processing to define the scale invariant structure in ECG, EEG, MR, and X-ray pictures. The scale invariant structures of inter-spike-interval of neuron firing, inter-stride-interval of human walking,

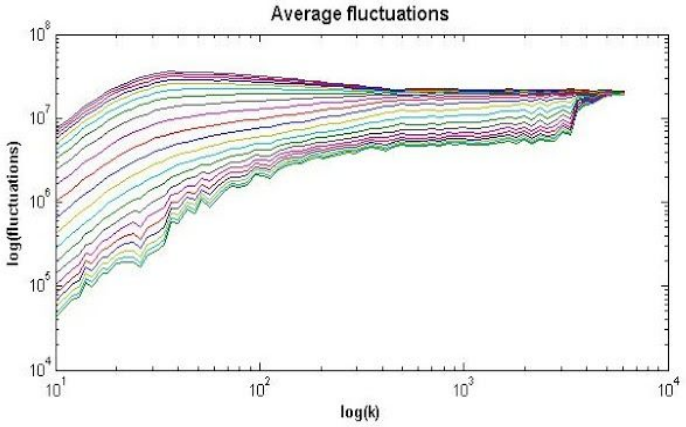
inter-breath-interval of human respiration, and inter-beat intervals of the human heart has differentiated between healthy and pathological conditions, and between different types of pathological conditions. Scale invariant structures are also found in spatial phenomena like the branching of the nervous system and lungs, and are able to differentiate between healthy and cancer tissues. Several reports during the last decade suggest that changes in the scale invariant structure of biomedical signals reflect changes in the adaptability of physiological processes and successful treatment of pathological conditions might change fractal structure and improve health. Fractal analyses are therefore promising prognostic and diagnostic tools in biomedical signal processing. Monofractal and multifractal structures of the biomedical signal are particular kind of scale invariant structures. Most commonly, the monofractal structure of biomedical signals are defined by a single power law exponent and assumes that the scale invariance is independent on time and space. However, spatial and temporal variation in scale invariant structure of the biomedical signal often appears. These spatial and temporal variations indicate a multifractal structure of the biomedical signal that is defined by a multifractal spectrum of power law exponents. As an example, age related changes in the scale invariant structure of heart rate variability are indicated by changes of the multifractal spectrum rather than a single power law exponent. The width and shape of the multifractal spectrum can also differentiate between the heart rate variability from patients with heart diseases like ventricular tachycardia, ventricular fibrillation and congestive heart failure. The multifractal structure of heart rate variability is therefore suggested to reflect important properties of the autonomic regulation of the heart rate. Furthermore, the multifractal spectrum of endogenous brain dynamics and response times is more sensitive to the influence of age and cognitive performance compared to a single power law exponent alone. Furthermore, the multifractal structure of EEG and series of inter-spike intervals have been able to differentiate between the neural activities of brain areas. Multifractal analyses might therefore be important as a computer aided tool to increase the precision of neurosurgeries. The main aim of the present tutorial is to introduce a robust analysis called the multifractal detrended fluctuation analysis (MFDFA) that can estimate the multifractal spectrum of power law exponents from a biomedical time series.

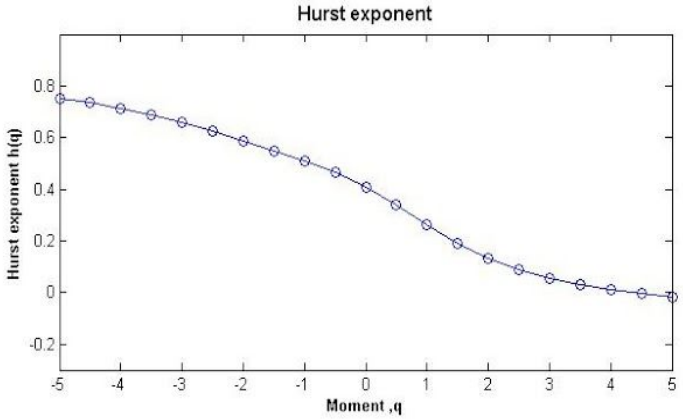
4.2. Parameters used for analysis

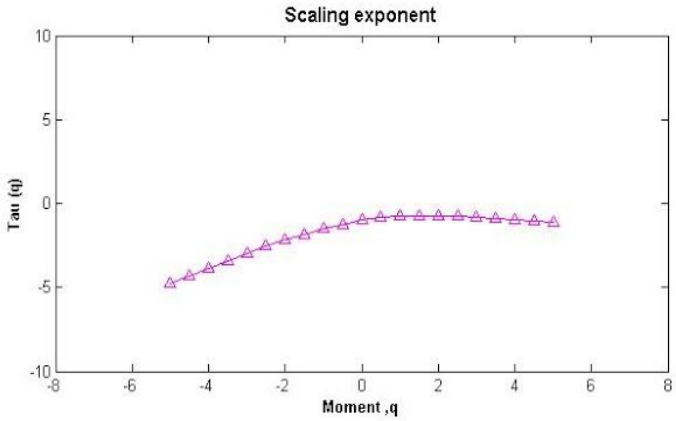
The following parameters were used while MFDFA was performed.
The maximum scale was set to 256 and moment was varied from -5 to 5 with intervals of 0.5
Order 1 polynomial was used for detrending.

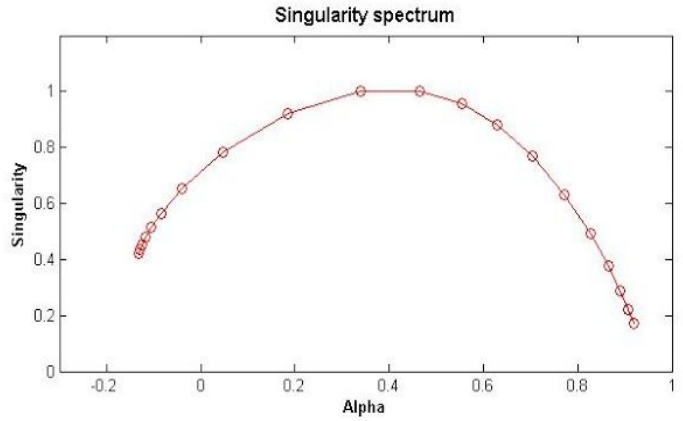
4.3. Results

The results for the time series data (Terapon) have been tabulated in Appendix 1. The following are the graphs for a single sample of Terapon.









4.4. Inference

As we can see from the above figure, the terapon sound is multifractal in nature. The singularity spectrum indicates the amount of multifractality. The wider the spectrum the more multifractal the signal. The spectrum is right-skewed, later we will see some associated parameters which are calculated.

5. Surrogate analysis

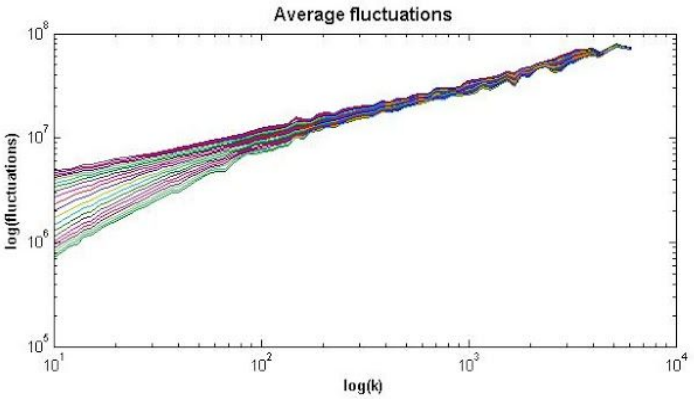
In general, two different types of multifractality in time series can be distinguished: (i) Multifractality due to a broad probability density function for the values of the time series. In this case the multifractality cannot be removed by shuffling the series. (ii) Multifractality due to different long-range (time-) correlations of the small and large fluctuations. In this case the probability density function of the values can be a regular distribution with finite moments, e. g. a Gaussian distribution. The corresponding shuffled series will exhibit non-multifractal scaling, since all long-range correlations are destroyed by the shuffling procedure. If both kinds of multifractality are present, the shuffled series will show weaker multifractality than the original series.

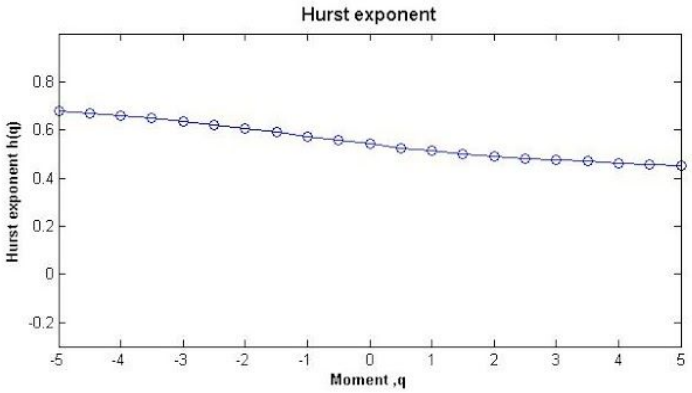
5.1. Shuffling of the time series data

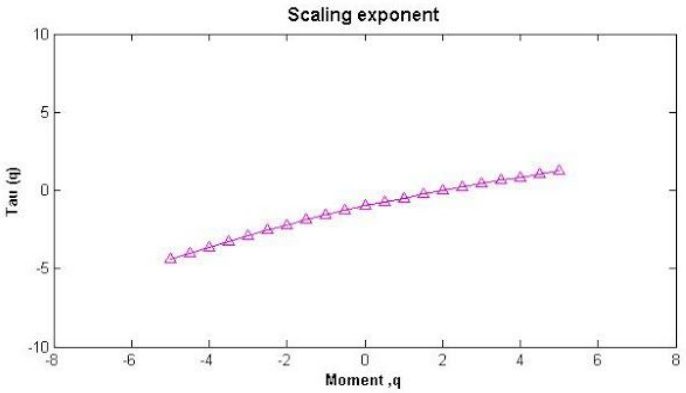
The time series data is randomized to destroy all long-range correlations. The randomization can be easily achieved by using the ‘randperm’ function in Matlab, which randomizes the indices of the time series data. This shuffled series is subjected to MFDFA analysis with parameters same as the time series data.

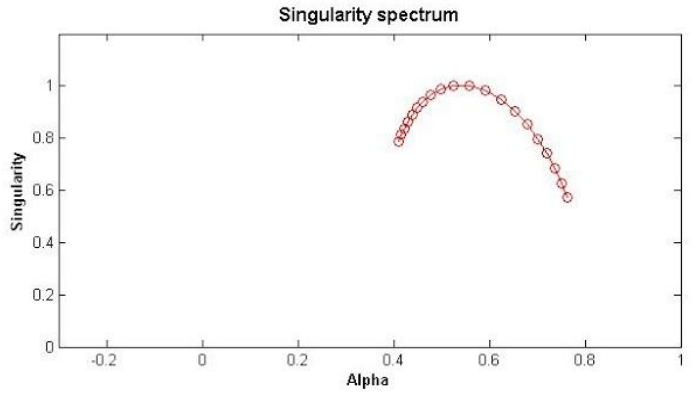
5.2. Results

The results for the shuffled time series data (Terapon) have been tabulated in Appendix 2. The following are the graphs for a single sample of Terapon.







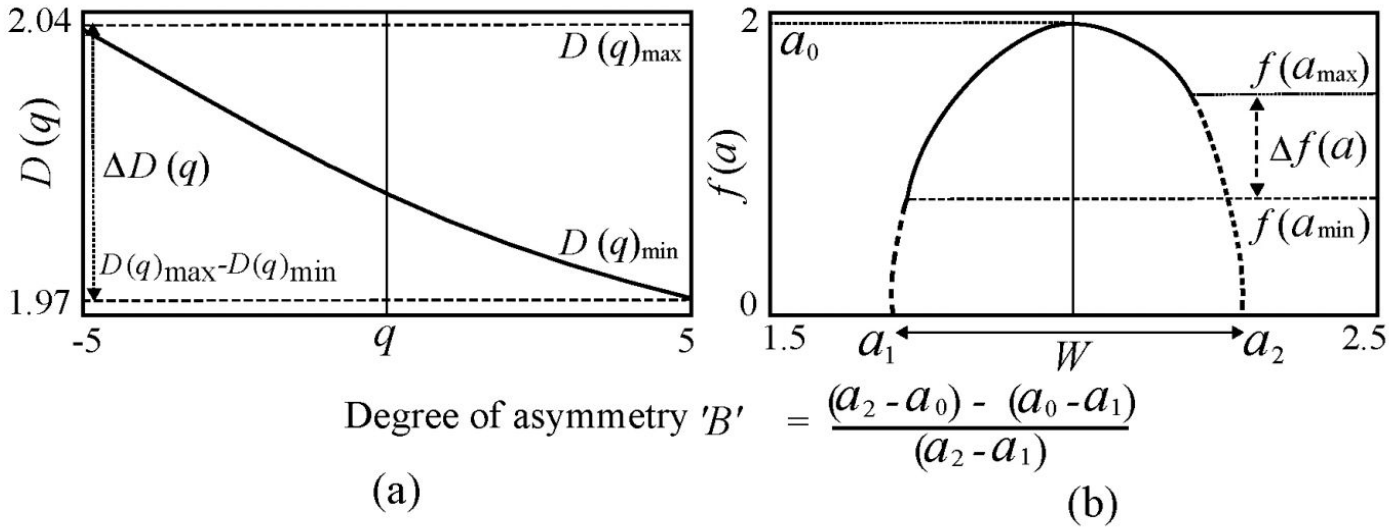


5.3. Inference

In the above figure we see the graphs associated with the shuffled time series data. We can clearly see the difference in the singularity spectrum. Here we see a narrower spectrum compared to the a previous time-series figure, which indicates the reduction in multifractality. Ideally only a point would have existed on the singularity spectrum indicating an monofractal signal, but here due to the broad probability spectrum we see a narrower spectrum.

6. Singularity spectrum analysis

In order to distinguish the multifractal spectrum f (α) quantitatively, it is convenient to calculate the width of the spectrum W so as to measure the overall variability. A wider f (α) spectrum is indicative of larger W, denoting multifractality. Such a situation reveals a heterogeneous seafloor. In the case of a monofractal set, W would be small and tending to zero. The spectrum will converge to a single point signifying a homogeneous seafloor. The other parameter B measures the asymmetry of the curve and shows the dominance of low or high fractal exponents. The value of B is zero for symmetric shapes and positive or negative for right or left-skewed shapes, respectively. A left skewed spectrum denotes low fractal exponents dominating the distribution, while a right-skewed spectrum implies dominance of high fractal exponents. Thereafter, the values of αmin and αmax are estimated to obtain the parameter f (α) as
f (α) = f (αmin) − f (αmax). |f (α)| defines the undulation or instability of the system under study. The degree of undulation or instability is minimum for the smallest f (α)(≈ 0).

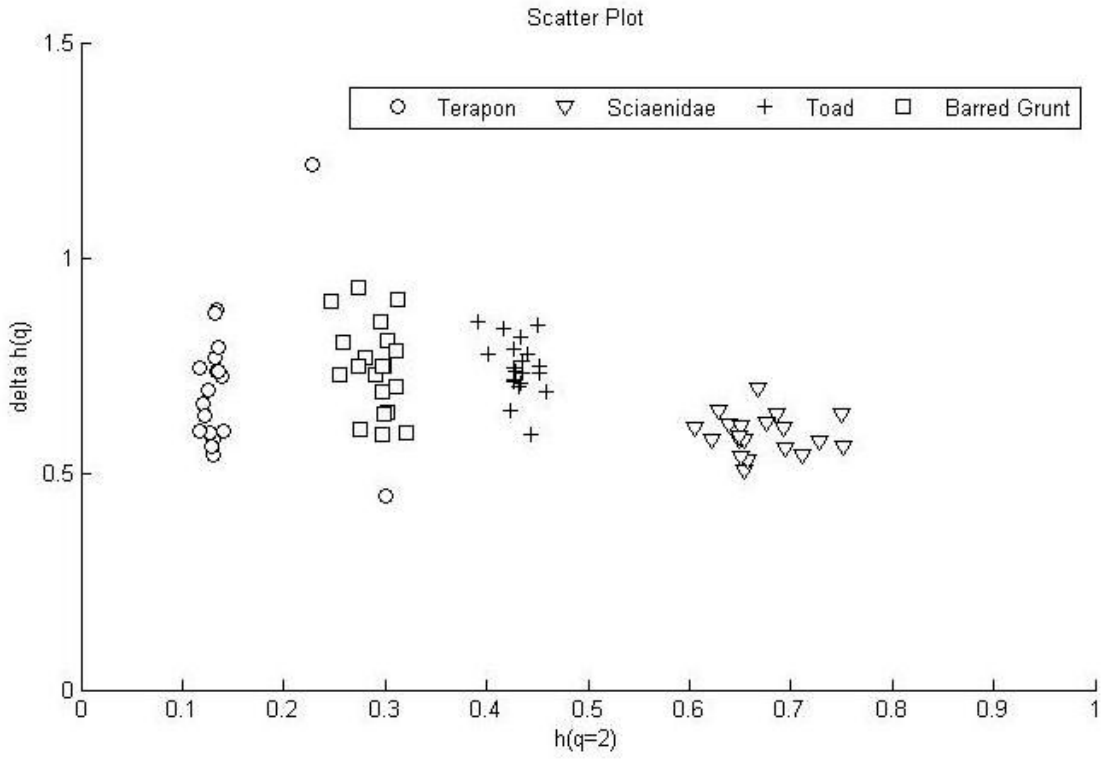


With the above analysis we can differentiate between species having similar values of $h(q = 2)$ and Δhq values.

7. Conclusion

This study clearing indicated all the fish sounds involved in the present study are multifractal in nature. MFDFA has the potential to analyse fish sound time series revealing the presence of long-range power-law correlation properties in the data. The long-range power-law correlations indicated the broad range of scaling exponents are required to describe the complexity. These time series signals hence have a small amount of multifractality is also contributed by the broad probability density function.

Below we see the scatter plot of species using $h(q = 2)$ and $\Delta h(q)$. We can see clear clustering patterns emerging. With these two features and the spectrum parameters calculated in the previous section I believe the species could be easily classified in a 5-dimensional space.



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9. Appendix 1

Fish	Timing	seconds		
Terapon	Start	End	$h(q=2)$	$\Delta h(q)$
GRAND-ISLAND_20140403_183000	14.05	14.35	0.2279	1.2188
	74.75	75.05	0.132618	0.769325
	76.4	76.7	0.133046	0.879008
	81.75	82.05	0.138895	0.726579
	57.9	58.2	0.135111	0.793848
	56.8	57.1	0.131383	0.870775
GRAND-ISLAND_20140403_160000	106.6	106.9	0.134266	0.736236
	92.45	92.75	0.133868	0.736536
GRAND-ISLAND_20140403_153000	26.5	26.8	0.134819	0.738242
GRAND-ISLAND_20140403_180000	85.6	86	0.120491	0.66271
	63.5	63.9	0.13023	0.580414
GRAND-ISLAND_20140403_164500	21.45	21.85	0.140996	0.598738
	28.7	29.1	0.130007	0.543905
GRAND-ISLAND_20140403_163000	14.85	15.21	0.125228	0.694786
GRAND-ISLAND_20140403_170000	33.75	34.05	0.299971	0.448371
GRAND-ISLAND_20140403_154500	4.05	4.45	0.128193	0.562776
	32	32.4	0.126378	0.59733
GRAND-ISLAND_20140403_171500	103.98	104.38	0.116829	0.747586
	98.95	99.35	0.116908	0.599842
	83.4	83.8	0.12219	0.637011

10. Appendix 2

Fish	Timing	seconds		
Terapon (surrogate)	Start	End	$h(q=2)$	$\Delta h(q)$
GRAND-ISLAND_20140403_183000	14.05	14.35	0.468576	0.215888
	74.75	75.05	0.479582	0.245562
	76.4	76.7	0.482642	0.196081
	81.75	82.05	0.504475	0.212971
	57.9	58.2	0.491073	0.204655
	56.8	57.1	0.499037	0.216594
GRAND-ISLAND_20140403_160000	106.6	106.9	0.511345	0.143257
	92.45	92.75	0.48423	0.132475
GRAND-ISLAND_20140403_153000	26.5	26.8	0.527815	0.11841
GRAND-ISLAND_20140403_180000	85.6	86	0.477364	0.144532
	63.5	63.9	0.49987	0.079261
GRAND-ISLAND_20140403_164500	21.45	21.85	0.501544	0.046151
	28.7	29.1	0.509239	0.06435
GRAND-ISLAND_20140403_163000	14.85	15.21	0.521661	0.130017
GRAND-ISLAND_20140403_170000	33.75	34.05	0.447461	0.037026
GRAND-ISLAND_20140403_154500	4.05	4.45	0.477908	0.104768
	32	32.4	0.476797	0.121316
GRAND-ISLAND_20140403_171500	103.98	104.38	0.492717	0.195327
	98.95	99.35	0.465938	0.086296
	83.4	83.8	0.516902	0.143099

11. Appendix 3

The following is a flowchart associated with the above study.