ISSN: 2834-7706

Reveiw Article

Journal of Mathematical Techniques and Computational Mathematics

Novel Spectral Approaches in Mathematical Bioacoustics Based on Real Time Analysis and Modern Computational Mathematical Techniques Using Digital Signal Processing and Analog Signal Processing Hardware (Review Lecture)

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Submitted: 2024, Feb 09; **Accepted:** 2024, Mar 01; **Published:** 2024, Mar 12

Citation: Adamovich, E. D., Gradov, O. V., Orekhov, F. K. (2024). Novel Spectral Approaches in Mathematical Bioacoustics Based on Real Time Analysis and Modern Computational Mathematical Techniques Using Digital Signal Processing and Analog Signal Processing Hardware (Review Lecture). *J Math Techniques Comput Math, 3*(3), 1-11.

Abstract
This review publication is an expanded version of the 2015 lecture at the III Moscow Seminar on Mathematical Bioacoustics and Analog Signal Processing in Physiology. Unlike the original 2015 version, this version includes developments by E.D. Adamovich and F.K. Orekhov, as well as a number of graphic materials of historical value. The work proposes new principles or approaches for multifactori/multimodal analysis of various bioacoustic signals based on N-dimension complex spectral analysis of different (bio) physical variables - "bioacoustic fingerprinting" and "bioacoustic footprinting". Hadware-based technical examples of possible uses of this approache are given for the breef annotation in the text of this lecture.

Keywords: Mathematical Bioacoustics, Bioacoustic Fingerprinting, Bioacoustic Footprinting, Real Time Spectral Analysis, Digital Signal Processing, Analog-To-Digital Conversion, Cepstral Processing, Phase and Saphe, Spectral Entropy of Signal, ASP.

1. Introduction

1.1 The Main Problems of Mathematical Bioacoustic Analysis

Despite the decades that have passed since the beginning of automated work on the bioacoustics of marine fauna, the most common analysis tool is representation in amplitude-time (oscillogram), frequency-amplitude (spectra and amplitude-frequency characteristics) and frequency-time (sonogram/ dynamic spectrogram) coordinate systems. Therefore, the main accepted models for describing the properties of a bioacoustic signal are models (and, consequently, methods) based on simplified concepts of amplitude and frequency modulation (AM and FM, respectively) borrowed from radiophysics [1-3]. The proliferation of computer acoustic spectrum analyzers, available to any specialist who has a computer with a high-quality sound card or other ADC (analog-to-digital converter) with very average technical characteristics, starting in the 1990s led to a situation where widespread software, which in most cases includes only analysis algorithms working in the above coordinate grids, began to "dictate" data analysis technologies to bioacoustics who do not fully possess programming skills and advanced mathematical tools necessary for a deeper understanding of processes at the physical/biophysical level [4-7]. As noted already in the 1990s "this ease of access increases the potential for incorrect methods or misinterpretation of results [8]." The only way out that logically followed from this state of affairs at that time was the transition from data analysis to their identification (using databases or one with another - previously identified) and comparison without taking into account their specificity and relevance to environmental, ethological, hydroacoustic and other conditions environment and their physiological generation, the same work proposes software for cross-correlation analysis of bioacoustic signals, which "is a candidate for replacing or complementing the visual comparison of spectrograms and their multidimensional analysis, being a search method for comparing sounds [8]. With the increasing availability of software with built-in cross-correlation methods, the analysis procedure is becoming accessible to biologists who may not have extensive knowledge of acoustics." A process equivalent to that occurring at the same time in spectrochemical analysis occurred, when the introduction of computer-aided analytics (COBAC) technologies and the spread of the principles of spectral analysis into routine analytical chemistry (where specialists working from first principles were absent) led to the replacement of the "old school" » spectrochemists with its successes in meaningful decoding of spectra came a young galaxy of specialists in automated identification, replacing the concepts of "decoding", "establishing physical correspondences" with the concepts of spectral fingerprinting (in almost all common spectral methods) and then with spectral footprinting [9-14].

A significant imprint was left by methodological inertia and a stereotypical approach to data analysis (uniformitarianism towards early sources analyzed by some method or technical complex, for reproducible comparison with which it is necessary to copy it multiple times in all works studying the object studied using it). As a result, despite the fact that any computer is indifferent to the variables and descriptors calculated on it, after the advent of the PC and, especially, IBM-PC-compatible platforms interfaced with sound cards and ADCs of sufficient capacity, the first emulated bioacoustic devices reproduced on them devices were sonographs also known as dynamic spectrographs, which visualized the dependence of the spectrum amplitude frequency dependence on time [16,17]. The subjectivity of comparing sonogram graphs visually, as well as machine recognition of graphic images of sonograms using neural networks, but in the absence of identifying descriptors other than those visually observed, was emphasized back in the 1990s, however, palliative and conventional solutions were chosen ad hoc, for convenience implementations did not reveal the array of heuristically valuable information that characterized the bioacoustic signal. The claims in the article "there have been some attempts to reduce subjectivity and increase the repeatability of this approach, for example by tracking sonograms on paper and examining areas of overlap or inconsistency using statistical data," should not be taken seriously, since statistical processing on descriptors that do not carry sufficient comprehensiveness information about the process does not bring new and sufficiently complete information for its qualitative description [18]. Despite this, and in subsequent work leading to the creation of bioacoustic control tools based on neural network algorithms or other methods of clustering and automated classification, the variables usually did not differ from amplitude and frequency, and models built on their basis could not in any way differ from AM- and FM-like simplifications.

Let us illustrate the last thesis with a number of representative examples, deliberately not specifically considering a number of early works that directly indicate the time-frequency nature of the analysis (even when we are talking about fairly advanced DSP methods - such as the Hilbert transform, autocorrelation tone detection, cepstral and wavelet analysis, Wigner-Vill transform for the analysis of non-stationary signals, etc. [19]). One of the first works in the field of publicly available extended analysis of measurements of bioacoustic characteristics (these measurements, obviously, are primary recording files) was work which described the LMA software, designed for time-frequency analysis of significantly noisy and harmonic or nonlinear distortion bioacoustic data [20]. LMA analyzes the number and location of dominant frequency or pulse-time ranges based on amplitude extrema, i.e. at a threshold depending on the amplitude distribution in the corresponding segment. LMA algorithms also carry out parameterization that characterizes the amplitude distribution along time-frequency coordinates - as medians and the 1st and 3rd quartiles of the total amplitude, and also determine the statistical values of amplitudes and their distribution along the time axis (initial value, minimum, maximum, modulation). It is quite obvious that LMA is a more statistical package than a DSP-oriented package, which does not extract information by analyzing the source data, but calculates statistics on data already presented in an accessible format for analysis. Another, more recent work on the automatic analysis of acoustic parameters proposes to implement an assessment of the fundamental frequency and statistically dominant frequency ranges, on the basis of which to calculate the distribution of spectral energy / power (which, in contrast to early subjective types and analysis techniques, is a very objective additive criterion), but at the same time, the only reference criterion even for two-channel files\recordograms is the frequency or pulse density per second [21].

Phase and other signal characteristics are ignored even in cases where they are significant for the energy analysis of bioacoustic signal files, although for specialists working with MATLAB, often found in bioacoustic group techniques extraction of these characteristics is not difficult (for example, see our computer-based modular analyzer of entropy, noise quality and phase with post-processng and analysis of bioacoustic signals in MATLAB on Figure 1) [22]. As a consequence of the limited array of parameters at the stage of primary processing of measurements (and the measurements themselves), the arrays of compared values in comparative analysis are limited - in particular, in the correlation analysis of the bioacoustic signal, and therefore in the methodology for automated classification of bioacoustic data. The cross-correlation method of analysis, used along with the PCA principal component method in sound classification, in particular cases of bioacoustic applicability comes down to the analysis of the frequency coordinate in time (and in power) and uses the formalism of normalized frequencies in clustering [23]. The correlation analysis of the formant structure in mammalian vocalizations is also of a purely frequency nature, based on the metrology of instantaneous frequencies, frequency bands and subranges, frequency modulation while taking into account the analysis of the autocorrelation function [24]. The result is obvious: with monoparametric (frequency) analysis, cross-correlation of spectrograms in bioacoustic analysis gives way to target parameters and automation of the study of patterns is replaced by automation of identification only with known parameters [25].

Figure 1: Computer-based modular analyzer of entropy, noise quality and phase with post-processng and analysis of bioacoustic signals in MATLAB, EDSW, "Fractan" and "AutoSignal" software (GEOKHI RAS, 2010).

1.2 Multifactor / Multimodal Biological Interpretation or DSP Identification Only?

Let's illustrate this. As is known, methods of image recognition and, in essence, semantic decoding and group identification based on ethological characteristics can be applied to bioacoustic whistles within the framework of fairly widespread software (such as the Dolphin software) [26]. This is a rather complex and time-consuming task, so no one is specifically addressing it, not allowing thoughts about expanded population screening on a bioacoustic basis (zoopsychological and population genetic with reference to the extended phenotype). Therefore, in the newest and most popular products due to their simplicity and publication efficiency, these capabilities are not emphasized. There is no need for an expanded pool of variables if there are no tasks extended in relation to standard approaches (solvable by the existing pool). The main part of modern clustering methods or neural network methods and software for bioacoustics is based on the subjective selection of criteria by the primary operator, that is, the so-called "supervised learning", while truly objective classification software should work on the principle of "unsupervised learning", itself selecting fundamental comparison criteria. The absence of this most important feature is currently a characteristic quality of ad hoc bioacoustic work performed. "After manual selection we trained an artificial neural network to automatically collect events from the recordings. Using hidden Markov models, we achieved at least 70% correct identification "the size of the repertoire was first assessed subjectively [27]. (Based on auditory and spectrographic patterns) on one of a large number of temporal types. for each call type, the preliminary mean was calculated the mean values were used for clustering" "a signal/song element is defined as the smallest (visually) distinguishable element of the spectrogram" "classification of a new sample is carried out in a Bayesian way [28,29]. Effectively estimating posterior clustering probabilities... for classifying new patterns" or "the results showed a typical trade-off of speed versus accuracy... the best algorithm was inserted into underwater audio recording and signal detection systems" [30,31]. How can one expect an objective massive analysis from a network into which subjectively selected parameters with palliative/compromising threshold values for an incomplete array of variables characterizing the signal are included at the stage of its creation? In the most progressive works condemning the impracticality of identification "by ear", which propose means of automatic detection based not only on temporal and spectral properties, but also on the properties of sequences, that is, sequences of signals the operation of a computer is not fundamentally different from the operation human ear and perception - since, also, like the latter, it does not distinguish between phase and other special features or signal descriptors in variables other than frequency and intensity [32]. In objective, from the point of view of the energy approach, works specifically indicate, in particular, that "most of the work on automated identification was carried out under supervision - depended on the preparation of data labeled by a person" and that in the optimal case, an "unsupervised approach without label pre-training" is needed data" [Ibid] the criterion and the only variables of ab initio analysis are amplitude, frequency and time, that is, clustering occurs in the most anthropomorphic and even anthropomimetic mode [33].

In the case of cepstral processing (similar to the chemical cepstrocsopy based on the setup, provided at the Figure 2), the situation changes a little: we get several new variables, but they duplicate the known ones in accordance with the needs of the new ideology of analysis [34]. These variables, by definition (definitively) are "saphe" - an analogue of phase and cepstral time or "quefrency". Any bioacoustic signal contains fundamentally extractable information about the phase, but in most methods, as indicated, it is neglected. A similar nuance works in the case of cepstral analysis of a bioacoustic signal. Phase information is extracted and the phase spectrum is formed in the case of complex cepstra (especially when restoring the original signals from convolution), which is synonymous with the method of homomorphic deconvolution or homomorphic filtering [35,36].

Figure 2: Elementary multimodal acoustochemical and bioacoustic (entomological) spectrometer with advanced spectral signal processing. General view of the device with a control panel and an ADC placement unit. The universal serial bus (USB) inputs leading from the ADC to the PC are visible (ICP RAS, Department of Dynamics of Chemical and Biological Processes, 2011). This device can also be used as a bioacoustic signal cepstrometer with ZLAB ADC-DAC.

It is also known that for minimum-phase signals, cepstral spectral coefficients can be obtained directly from the power spectrum estimate, and only in this case do cepstra and complex cepstra produce virtually equivalent results, which is due to the fact that both methods are based on the inverse FFT transform (inverse Fourier transform) of the logarithmic power spectrum. Thus, cepstral analysis in the case of bioacoustic processing can provide no more and no less information than spectral analysis implemented over the entire array of variables, including phase. However, a review of currently available commercial products - such as the AVISOFT software and hardware complexes, often used by both terrestrial bioacoustics and hydroacoustics, but stopped at the stage of a progressively expanded digital sonograph [37,38]. SYRINX, SCREECH and others as well as many other representatives of proprietary software (Adobe Audition, WaveLab), often used by bioacoustics instead of specialized software, shows that the functions of calculating the phase spectrum, not to mention more complex processing methods they are usually absent or are in illustrative form [39,40]. Probably as a consequence of this, in most of the reviewed works in the thematic trend, these approaches are also absent [41-48]. Low-budget solutions introduced long ago did not solve the problem (due to low budget?) but new cross-platform or UNIX-oriented / Linux-oriented software solutions with open source and a free distribution policy do not consider "unpopular" phase type descriptors and do not have the means (or utilities) for analysis based on criteria other than human hearing [49,50].

1.3 Are Simplified Approaches Good for Phase-Complex Bioacoustic Signals?

Simplification of models does not go unpunished for their quality. Ignoring the phase at the stage of selecting variables in bioacoustic analysis leads to a number of paradoxes that are akin to quantum uncertainty and cannot be eliminated otherwise than by multicriteria optimization methods, leading to palliative decisions - a compromise that is not beneficial from a metrological point of view (unless, of course, return the phase back to the limits of consideration). Recognizing that "animal vocalizations are not periodic, frequency-modulated signals," but limiting himself to a two-dimensional approximation where "the type of signal simultaneously varies in two dimensions, time and frequency," Beecher, contrary to the obvious, does not introduce additional variables, but postulates a formalism, or rather a concept, in which "spectrographic measurements are constrained by the 'uncertainty principle'" and "to improve the accuracy of a measurement in one dimension, we must sacrifice the accuracy of a measurement in another dimension" [Ibid] [51]. Beecher makes a logical conclusion within the framework of this approach that "a compromise is inevitable" and "for any particular frequency-modulated aperiodic signal there is an intermediate-optimal spectral bandwidth setting equal to the square root of the average rate of change of the measured signal" [Ibid]. It seems rational, appealing to common sense, to exclude the uncertainty principle from the analysis of signals with low-frequency characteristics that are observable even without ultra-high-speed oscilloscopes, but for this we need to turn to the phase and phase spectrum. It is known that in the transactional interpretation, which appeals to the principle of uncertainty, the amplitude is determined by the degree of phase coincidence. Even if we consider a bioacoustic signal (which, it must be said, does not make sense in a practical context) as a wave function, which in the classical case of potential is a measure of kinetic energy, with a spectral distribution invariant in a given taxonomic or other category, this should be associated with a change in the wave phase functions. Moreover, the concept of kinetic energy density, which reflects the change in the latter, definitively includes both a change in module and a change in phase! The need to introduce uncertainty for the analysis of bioacoustic signals is not obvious from the standpoint of analysis using spectrographic digital cross-correlation (SPCC) in which frequency, amplitude, and time are simultaneously analyzed [8]. The most advanced versions of SPCC, in particular, the SPCC-PCO algorithm which operates both on the time-frequency recordogram of the signal and its duration within the framework of principal component analysis (analysis of the frequency coordinate in time using the PCA method in bioacoustics) and weighted harmonic components (i.e., harmonic parameters, to use the slang of sound engineers-acoustics), allowing emphasis, rather than smoothing out the differences between signal types in the n-dimensional space PCO takes into account, or more precisely, must take into account, by definition, also the phase [23,52]. It is well known that the energy exchange between harmonics depends on the phase relationship: in a system with frequency dispersion, the phase velocities are different and the relationships between the phases change at a very high speed, without supporting the nonlinear effects that arise in the presence of phase matching. For obvious reasons, when changing the reference point (the recording time of bioacoustic oscillograms), the initial phases of the harmonics, that is, the phase spectrum of the signal, will change (the phase spectrum of the signal can be interpreted as a set of the initial phases of all harmonics), and the amplitudes of the harmonics will remain constant. That is, signals with an equivalent amplitude spectrum in different clustering groups may differ with statistical significance in non-equivalent phase spectra. It should be noted that using the phase approach at low quantization and sampling values does not make sense, since the discreteness of the phase space is fraught with measurement artifacts, and the usual jitter of digital recording and oscillographic systems is definitively the phase jitter of the digital data signal and is visualized as a phase shift between ideal (either supplied or reference) and real signal (according to the ITU-T G.810 standard, the term wander is also adopted).

In this sense, the feature of a number of methods (including the above-mentioned SPCC-PCO in its bioacoustic explication) to analyze noise (see Figure 1) and signal-to-noise ratios, including the harmonic weighing criterion, is very justified [52]. From first principles (ab initio) it is necessary to take into account some properties of phase noise in electronic recording (eg, ADC) and generating (including DAC) means. It is known that there is a mathematically specific relationship between frequency and phase, as a result of which the principles that formally describe the deviation of frequency and phase (depending on time or frequency in the corresponding coordinates) are physically interrelated, and frequency is considered in this case as the rate of phase change. The phase shift is measured with a frequency reference - in a given frequency band or a specific individual sideband. A feature of noise, from the point of view of bioacoustics, is the content of an almost full range or stochastic set of phases of spectral harmonics. However, as is known, there are also underwater noises, which, in the phase-frequency characteristic, in most recordings that are not equipped with artifacts, differ from bioacoustic signals, however, the latter can also be unrecognizable noise and recording artifacts. When monitoring the noise parameters of the ocean various sources of noise are permanently recorded, which both affect marine fauna (including its acoustic communication) and are generated by it [53-58]. Non-directional sound recording does not allow identifying the source of noise (regardless of its biogenic, geological or technogenic nature), which also directly follows from one of the meanings of the term ambient. Therefore, in the diagnosis of a bioacoustic environment, there is a pronounced trend towards combining the identification of a sound source (sound source species analysis) and the determination of its spatial localization based on data and with reference to the data of its multi-position bioacoustic measurements / sound mapping (see Figure 3) [59].

Figure 3: Digital microprocessor azimuthal bioacoustic correlometer for microphone arrays with ADCs. Prototype development: Adamovich E.D. (2015).

These measurements are made by many differently localized microphones at known distances (microphone arrays) for comparative differential signal processing [60]. In this case, phase noise can be filtered with a matched filter. However, the principles of differential comparative analysis in microphone arrays are directly physically based on phase delay measurements, being, in the elementary case, somewhat similar to measurements of binaural characteristics of auditory perception. Since human perception ignores phase information, as a rule, few people work specifically on this, however, if we move away from direct analogy to anthropocentric perception when designing and analyzing bioacoustics problems, then phase information will turn out to be very significant. Thus, the characteristics of phase spectra are essential for perception in dolphins, since it is associated with the binaural phase difference at the points of the auditory canal and inner ear, and, moreover, Dolphins use phase patterns in emission and reception to increase the acoustic contrast between echo intensity and sound interference [61,62]. As is known, complex acoustic systems can be modeled using digital filters, which makes it possible to model and program most frequency and phase responses in auditory perception [63]. Therefore, there are no physical and technical grounds for anthropomorphism in the aspect of simplifying the perception model and phase biomimetic signal-to-noise filtering. The authors of the work note that not all animals have directional hearing based only on differences in amplitude between the ears, and also that the use of the difference in the time of arrival of the signal between them, understood as phase, is a fairly common and more resistant to sound degradation means of detecting directionality, and on natural neural networks such recognition (based on the phase descriptor) is not inferior in efficiency to amplitude decoding [64].

Many examples of such bioacoustic machinery can be given. Phase models for determining pulse localization in neural network implementation have been known for a long time [65]. In AER analysis (auditory evoked response), the polarity of the response when switching the phase by 180° and the corresponding delays are often analyzed [66]. In it is especially emphasized that amplitude signals degrade faster, and organisms that use phase methods of perception are able to more rationally navigate the acoustic field, even when amplitude perception no longer provides the required information [67]. The degradation of signals and their direction during dispersion in space (this is the cause of disorder in ambient noise) is more successfully overcome by animals with the perception of phase differences. In the case of ambient noise in shallow water when close to reflective surfaces of the bottom, phase recognition is extremely important [68]. This would not be worth talking about in the context of communication if there were not some correlation between directionality as a physical criterion (directional diagram) and the development of the sensory parameters of the body and its nervous organization. This requires the use of bioacoustic correlometers and source orientation analyzers (Fig. 3, Fig. 4).The directional patterns of higher organisms are more optimized (in particular, in primates the signal is emitted more omnidirectionally than in humans, their highest representative according to neurophysiological criteria) [62,69]. In the case of radiation pattern varieties of communication, the phase shifts due to phenomena such as reflection from the surface (ground) and interference between the direct wave and the surface or reflected wave. This is critical for information transfer, which requires phase analysis to avoid chaos based on reverberation effects, etc. This is particularly true for marine mammals. Unfortunately, many studies were not carried out on them that were carried out taking into account the phase on other (simpler) organisms, but the ethological meaning of the analogy, taking into account the pulsed nature of phonation of both, can be demonstrated by several detached examples. Thus, for H. versicolor, phase-incoherent signals are less attractive to females, and a 50% phase shift, which is equivalent to 180°, reduces the efficiency of communication by 1/3 and even by V of the signal [70].

Figure 4: Multi-angle orientation comparative two-channel correlometer with a universal serial bus (USB) and built-in ADC. This instrument was developed by Gradov O.V. (with co-authors) in GEOKHI RAS in 2010. This instrument was reconstructed and modernized by Adamovich E.D. in 2014.

On the other hand, avoiding acoustic and mechanical resonance, a number of organisms in natural conditions use antiphase generation modes during acoustic signaling while other organisms use resonance as an integral and specific attribute of their bioacoustics [71,72]. Thus, monitoring biodiversity through diversity analytics of bioacoustic signaling should include phase analysis and signal phase spectroscopy [73]. Bioacoustic absorption spectroscopy, based on the study of sound absorption by the biomass of the ocean or other environment, can be given a certain semantically significant and communicatively interpretable meaning by applying the principles of phase analysis and directivity measurement using the latter [74]. This is especially sensitive for the last task in the presence of non-directional noise - ambient noise of the ocean, recorded not only by passive oceanic acoustic observatories, but also by corpuscular physical installations located in the ocean [75,76]. For any acyclic stationary conditions, that is, at least for subtidal systems (at a level below the tidal zone), methods for recording, archiving and analyzing measurements of bioacoustic parameters, without requiring feedback automation to adjust the level of location of the recording system and its detectors in the environment, is implemented simply, accessible and cheap [77].

Figure 5: Precision digital bioacoustic carrier modulation analyzer with universal serial bus (USB) and built-in two-channel ADC. The left indicator is a carrier wave indicator. The right indicator is the low-inertion nanovoltmeter. This instrument was developed by Gradov O.V. (with co-authors) in GEOKHI RAS in 2010. This instrument was reconstructed and modernized by Adamovich E.D. in 2014.

4. On the Benefits of Abandoning the Anthropomorphic Approach to the Recognition of Biosignals

In order to analyze bioacoustic signals from the point of view of systems and objects that perceive the signal in real conditions, that is, biological systems, we must move from the anthropomorphic approach to biomimetic analysis. Since, as stated above, many marine organisms have phase sensitivity, their recording spectra should be not only amplitude, but also phase. One should proceed from non-simplified models in order to obtain results that are not distorted by simplifications. In this regard, the distributions underlying classifications must be adequate to the principles of separation that underlie interspecific and ethological recognition in the natural environment (for example, predator / prey or male / female / young or aggressive / latent / neutral individual, etc.). To impose purely dichotomous systematizations on nature and, even more so, simplified forms of distributions when fitting (fitting, adjusting data) ad hoc is irrational. However, dichotomous sorting is the main system of choice in models of bioacoustic recognition in the presence of a predator [78]. In programs for acoustic identification of arthropods, probabilistic neural networks and parametric estimation of the probability density function using Gaussian systems are used (at all levels of the hierarchy - suborders, families , subfamilies, genera and species) [79]. Even in essentially biomimetic recognition systems - when classifiers or software clustering tools imitate recognition means of auditory images or echolocation systems (for example, dolphins), and fairly adequate biomimetic or neuromimetic algorithms are used (including genetic and evolutionary algorithms), nevertheless, they choose subjective weight functions, in particular, of a pseudo-Gaussian nature [80]. The specificity of methods and principles of analysis regarding objects is not taken into account, based on which approaches to data approximation should be selected, i.e. fitting to distributions. Models of bioacoustic or other communication are adequate to the behavioral conditions of the environment.

Therefore, recognition programs must be behaviorist-adaptive in order to correctly recognize, rather than adjust, data. In elementary applied statistics, it is well known that the nature of distributions depends on the type of events (successful or unsuccessful attack of a predator on a prey ceteris paribus - Bernoulli distribution, the number of females / males in a population - binomial distribution, time intervals between runs of specific prey when it is waylaid by a predator - exponential distribution , natural population mortality due to energy causes - Gompertz distribution, the number of fatal mutations in population autoreproduction - Poisson distribution, reliability theory in biophysical type systems - Weibull distribution, etc.). Therefore, the number of events in the bioacoustic case must be timed and colocalized with the systematics of the statistically corresponding distributions. If there is a correct interpretation and correct prediction of events on its empirical statistical basis, it is possible to produce statistical fingerprinting of events together with spectral or other metrology-oriented fingerprinting of the nature or source of events. In terms of its fundamental qualities, this approach is much more expedient than fingerprinting in frequency space (which does not carry ethological and causal information in principle) and a statistically non-adapted random ethological study.

5. Conclusion

Thus, to summarize, we can summarize the physically feasible methodology for analyzing bioacoustic signals in native conditions (including in real time and beyond the "purely acoustic", that is, audible or human-reproducible range) in the following form [81]. An automated classification system based on bioacoustic indicators, or rather, the qualifications of its user should not be subjective when using objective data:

➢ I. Understanding bioacoustic signaling as a means of communication (both interspecific and intrapopulation), take into account, at a minimum, those characteristics of the bioacoustic signal that are perceived and used in communication or have some other information value (for example, in the case of bioacoustic location). In particular, it is logical to use objective units of measurement (instead of conventional and normalized ones for human perception) [82].

➢ II. Monitor characteristics not in the range that is recorded by the human ear or modern means of low-frequency sound recording, but in the range to which the real harmonics of the signal extend [83,84]. If this corresponds to new descriptors associated with the interaction of high-frequency or low-frequency signal components with the environment, then the underlying physical effects should be taken into account when modeling wave propagation [85].

➢ III. Based on the properties of the signal, and not the processing features, since the introduction into the analysis of purely amplitude-frequency characteristics of wavelet representations and visualization based on scaleograms (scaleogram, scalogram) instead of sonograms as well as the introduction of new methods of Fourier analysis based on elliptical descriptors or replacing metrological frequency with cepstral time (quefrency) in cepstral analysis, introducing new entities, does not lead to the emergence of new information about the signal [86,87,88]. You can complicate processing systems as much as you like, but convolution systems without extracting new variables only reduce the heuristic value of information about the signal. Therefore, it is necessary to characterize the signal also by other complementary parameters - phase, radiation patterns for different variables (depending on which of them most objectively characterizes the flow of bioacoustic information), etc.

➢ IV. Take into account the properties of objects of bioacoustic communication or bioacoustic echolocation in circuits with feedback and as transceiver systems. The development of directional patterns during phylogenesis went along with the development of morphological differentiation of organisms, which cannot be ignored.

➢ V. To carry out not only simple recognition (even very multiparametric), but also linking to cause-and-effect relationships and the causal conditionality of a particular type of signal from a specific taxonomically recognized source, which will allow us to move away from simple identification (fingerprinting) to one interpreted within the framework of ethological, ecological, neurophysiological and "behaviouristic" automated methodology for research statistics.

➢ VI. Take into account environmental noise and be able to separate environmental noise from the noise of biological systems, based on fingerprinting their physical characteristics (technical noise, having a reliable physical character, can be easily distinguished: flicker noise is 1/f noise, white noise is 1/f[2]-noise, frequency flicker-modulation noise is 1/f[3]-noise, random frequency modulation during recording is 1/f[4]-noise), including phase and directional patterns (see above regarding defocusing ambient noise). Many biological and non-biological noise sources can be separated as parametrically distinct also using noisy signal entropy analysis methods (see Fig. 1) used in various fields applicable to bioacoustic data [89-94].

➢ VII. Rely on those types of signal modulation that are actually used by certain specific animals in bioacoustic signaling, defining them both from the point of view of the organism that is the source of the signal ("transmitter"), and from the point of view of the individual perceiving the signal ("receiver"), that is, not to be limited to standard AM and FM modulation (see Fig. 5) in approximations describing the biosignal, as has become popular in the last period.

➢ VIII. Without simplifying the set of variables, it should, however, be accessible and adaptively reconfigurable by the operator, a modular system (LabView type) for research, and not for routine tasks, allowing the introduction of an objective and comprehensive approach in situ at the same time [95].

Authors Contribution

1. Adamovich E.D. - design of bioacoustic instruments, semi-automatic text translation, photography of computational and computerized bioacoustic setups.
2. Gradov O.V. - conceptualization and text writing, project management, photography of computational and computerized bioacoustic setups.
3. Orekhov T.K. - aprobation of spectral aproaches and true real time spectral analysis in mathematical bioacoustics, collection of spectral libraries.

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