Archives of Acoustics Vol. 49, No. 2, pp. 189–197 (2024), doi: 10.24425/aoa.2024.148790

Research Paper

Assessment Effects of Humidification of Guitars by Complexity Measures of the Sound Level During Sustain

Robert STĘPIEŃ*, Piotr WRZECIONO

Institute of Information Technology
Warsaw University of Life Sciences
Warsaw, Poland

*Corresponding Author e-mail: robert_stepien@sggw.edu.pl

(*received August 23, 2022; accepted January 23, 2024; published online April 8, 2024*)

Air humidity significantly affects the sound of wooden instruments. The sound quality decreases when the instrument is exposed to low humidity for an extended period. Therefore, the instrument is treated with a humidifier to improve sound quality. This study aimed to verify the effectiveness of the humidification process by analyzing the quality of guitar sound with the methods used in signal complexity studies, such as Higuchi's fractal dimension (HFD), symbolic analysis, and empirical mode decomposition (EMD). The sound quality was determined by the sound levels measured before, during, and after the guitars' humidification. The methods used consistently confirmed the improvement of the guitar sound quality after the humidification process. Moreover, it was concluded that the sound quality changes irregularly during the humidification process.

Keywords: guitar; hygroscopicity; complexity parameters; acoustic measurements.

1. Introduction

Sound quality or the quality of an instrument is an essential consideration for musicians and those involved in instrument construction and maintenance. In the case of musical instruments made primarily of wood, the physical condition of this material is essential. It is described by some parameters, among which moisture content is one of the most important. This is because wood contains a high percentage of lignin, which is very hygroscopic (Gordobil *et al.*, 2021). A change in wood moisture content causes a change in acoustic parameters, e.g., density, Young's modulus, and other physical parameters. Changes also affect the structure of the wood itself, as very dry wood may crack easily (Rath, Staudinger, 2001). The problems mentioned have a significant impact on the musical instrument sound and its overall condition.

The acoustic guitar is an instrument made primarily of wood. The tree species used in the instrument are primarily spruce, cedar, and mahogany (Gore, 2011). Humidity affects not only the sound but also the tuning of this instrument. When the wood is too dry, the neck's geometry changes, causing out-of-tune sounds on the frets (Wrzeciono *et al.*, 2018). In addition, the moisture content of the wood in a guitar may vary with the season. For example, in Poland, wood drying is most noticeable during winter conditions (Wrzeciono *et al.*, 2018).

Luthiers deal with this problem in different ways. One solution is presented in the paper (Wrzeciono *et al.*, 2018), where a parametric analysis of guitar sound before and after humidification was performed. As a result, it was possible to determine several parameters, including the time of sustain, which varied significantly depending on the instrument's condition. However, linking the audible change in the swell to the measurement results remained a challenge. In this paper, we present methods to solve the mentioned problem.

During the experiments, the evaluation of the instrument's sound quality was carried out by its owner. However, the humidification process was conducted in the luthier's workshop, where the instrument was serviced due to excessively low wood moisture content. In such a situation, there is a possibility that the measured sound parameters do not support the subjective assessment made by the instrument owner. Conducting a double-blind test under such circumstances was impossible. So, measurements and analysis of the results had to be performed to determine whether a trend would correlate with the musicians' perceptions. A detailed study of changes was described in the paper by Wrzeciono *et al.* (2018). Through this study it was found that the most significant changes perceived in sound are related to the sounding time.

The objective of our study closely aligned with the evaluation procedures employed by musicians in assessing the sound quality of an instrument, where in normal operational conditions, musicians leverage the phenomenon of mutual excitation of strings. Consequently, it was necessary to conduct experiments with all strings attached. Therefore, our study aimed not to eliminate this phenomenon but to examine its quantitative changes.

2. Materials and methods

In a pilot study related to the parametric analysis of guitars, about 60 instruments were used before proceeding to a systematic multi-day experiment. All of the instruments tested had new strings attached. The tuning process was carried out using a specialized luthier's device that tunes an empty string to an accuracy of 0.1 cents.

Typically, moisturizing a guitar usually takes a week, and the effects of humidification are monitored daily (Wrzeciono *et al.*, 2018).

The measurement setup included a chamber sound box isolating the guitar from its surroundings, along with a microphone unit. The strings were excited by a free-falling arm containing a handle to prevent the arm from rebounding. Measurements of the sound level obtained by striking the strings with the arm were conducted with a set of microphones placed on the axis of the sound hole, at a distance of 15 cm from the guitar. The primary measurement was made with a PreSonus PRM1 microphone calibrated with a Sonopan KA-50 calibrator. In addition, the Rode NT1 microphone was employed as the second one to record guitar sounds with a low noise level.

The microphones were connected to a Focusrite Scarlett 2i2 2Gen audio interface, and the measurement system was calibrated with a signal from a 94 dB acoustic calibrator (Sonopan KA-50). Then, a recording of the guitar sound was made after striking the strings with the arm. A single recording consisted of ten strokes made every 60 seconds. The recordings were made at a sampling rate of 96 kHz and a bit resolution of 24 bits. Infrasound components were removed from the calibration and measurement signals by the Octave program's digital filter. The signal from the PRM1 microphone was used as a reference to calculate the sound level of the tested guitar. A detailed description of the measurement method and measuring instruments is presented in the paper by Wrzeciono *et al.* (2018).

Several parameters describing the guitar sound were also defined in that work. However, the sounding guitar time, denoted as T_{40}, was the most important one. The T_{40} parameter is the interval of time in which the sound level of the guitar, after impulse excitation, drops by 40 dB. A time window of 10 ms was used in the signal power calculation. In addition, infrasonic components were previously removed from the signal. However, the T_{40} parameter alone does not account for the change in the decay's nature (Wrzeciono *et al.*, 2018).

Therefore, further analytical work was undertaken to reconstruct the auditory impression. The study involved qualitative and quantitative analysis. Higuchi fractal dimension (HFD) and symbolic analysis were chosen as qualitative analysis, while empirical mode decomposition (EMD) was selected as the quantitative analysis.

Both HFD and symbolic method have been used to analyze biomedical signals for medical diagnosis and treatment evaluation efficacy (Gladun, 2020; Gomolka *et al.*, 2018; Pierzchalski *et al.*, 2011; Stojadinović *et al.*, 2020). Therefore, using these methods to analyze a relatively uncomplicated signal, such as the sound level of a guitar, should yield intriguing results. The problem of evaluating the effectiveness of the humidification process is analogous to assess the effectiveness of therapy. At its core, conditioning serves as therapy for the instrument.

The fractal dimension and the characteristics of the symbolic analysis allow, based on the analyzed signal, to determine the state in which the system generating the signal is present, thus enabling the detection of state changes. These methods allow to track changes in long signals through the use of moving window technique. Since the waveforms of sound levels concerning the registration of physiological signals are short, global (for the whole signal) values of fractal dimension and symbolic parameter were calculated. These calculated parameters give general information about the changes in guitar sound.

On the other hand, EMD is currently used in a wide range of topics in geophysics (Huang, Wu, 2008), oceanology (Zhou *et al.*, 2021), biomedicine (Khan, Pachori, 2021; Li *et al.*, 2021; Pierzchalski *et al.*, 2011), and engineering (Zheng *et al.*, 2021). The design of the EMD method gives a broader picture of the changes in the system under study. It is multiparametric and thus less synthetic than the previously discussed methods. The original decomposition into modes and the residue allow us to observe precisely what occurs in the sound level signal.

3. Signal processing

3.1. Brief introduction to methods of analysis

The humidification process significantly changes the shape and complexity of the sound pressure level (SPL) curve. Therefore, employing signal complexity analysis methods is justified. Three methods have been proposed and used here: HFD, symbolic analysis, and EMD. They represent different approaches to signal analysis. HFD is based on scaling law; symbolic analysis uses statistics; EMD is an iterative decomposition procedure. Thus, the convergence of results obtained by these methods confirms the notion of SPL analysis as a complex signal. Furthermore, the agreement of these results with listening evaluations validates the use of these methods for automatic evaluation and control of the humidification process.

HFD and symbolic measure are global. Their values allow determining only the level of complexity of the signal. On the other hand, EMD analysis provides more profound information about the changes that occur in the signal.

3.2. Higuchi's fractal dimension

HFD of the signal curve (Higuchi, 1988) measures the signal's waveform complexity and should not be confused with the fractal dimension in phase space (Mandelbrot, 1967). HFD, denoted as D_f, typically ranges from 1.0 (for a straight line or straight Euclidean curve) to 2.0 (for a curve with random amplitudes). The only parameter of Higuchi's algorithm is $k_{\max}$. It is the maximal rescale (time delay) integer parameter, which depends on the sampling frequency and signal length (Spasić *et al.*, 2005). In our study, the optimal value of $k_{\max}$ has a value of eight, because D_f has the least variance at this parameter setting.

From sampled in time signal: $X(1), X(2), ..., X(N)$, the algorithm constructs k new series X_m^k: $X(m)$, $X(m{+}k), ..., X(m{+}\text{int}((N-m)/k)k)$ for $m = 1, 2, ..., k$, where m is the initial time, k is the delay, and $\text{int}(r)$ is the integer part of a real number r.

For every $k = 1, 2, ..., k_{\max}$ the difference between shifted samples starting from the following m is calculated as:

$$L_m(k) = \frac{1}{k}\left(\sum_{i=1}^{\text{int}\left(\frac{N-m}{k}\right)} \left|X(m+ik) - X(m+(i-1)k)\right|\right) \cdot \frac{N-1}{\text{int}\left(\frac{N-m}{k}\right)k}, \tag{1}$$

where N is the total number of samples.

Next, the mean of the k values $L_m(k)$ for $m = 1, 2, ..., k$ is calculated as:

$$L(k) = \frac{1}{k}\sum_{m=1}^{k} L_m(k). \tag{2}$$

$L(k)$ satisfies the scaling law:

$$L(k) \propto k^{-D_f}, \tag{3}$$

where exponent D_f is HFD. This relationship is reduced to linear form:

$$\log(L(k)) \propto D_f \log\left(\frac{1}{k}\right). \tag{4}$$

Hence, the value of the fractal dimension D_f is calculated by a least-squares linear best-fitting procedure.

3.3. Symbolic analysis

The symbolic analysis uses the methodology applied in information theory (Stone, 2022), which defines many parameters of signal complexity, i.e., entropies and related measures (Ribeiro *et al.*, 2012; 2017). However, in this paper, we propose to use a more specific parameter whose mathematical description is close to the average codeword length (Johnson Jr *et al.*, 2003).

The construction of the parameter uses the statistical distribution of symbol sequence representing the falling and rising slope of the signal (Stepien, 2011). The general idea is to encode the changes in signal between successive samples with symbols "0" and "1":

$$c(i) = \begin{cases} 1 & \text{if} \quad X(i) \geq X(i-1), \\ 0 & \text{if} \quad X(i) < X(i-1). \end{cases} \tag{5}$$

The symbol "1" denotes an amplitude increase, while the symbol "0" denotes an amplitude decrease between successive signal samples. Thus, rising edges of the signal correspond to "1" sequences, and falling edges to "0" sequences. In this way, the monotonicity of the signal is encoded. Hence, sequences comprising only "1" or "0" symbols are called mono-sequences here. We denote the length of the mono-sequence corresponding to the rising slope by $l(\{1\}^*)$, while that of the falling slope by $l(\{0\}^*)$.

To estimate the probabilities $p(l(\{1\}^*))$ and $p(l(\{0\}^*))$ of occurrence of mono-sequences of consecutive lengths let us encode the signal according to the rule (Eq. (5)). Then, count the encoded signal's mono-sequences according to their length and divide by the total number of mono-sequences of a given type.

Our signal characteristic is the sum of mean values of mono-sequences' lengths in the coded signal, which are calculated as:

$$\begin{aligned} L_1 &= \sum_{l=1}^{l_{\max}} p\left(l\left(\{1\}^*\right)\right) l\left(\{1\}^*\right), \\ L_0 &= \sum_{l=1}^{l_{\max}} p\left(l\left(\{0\}^*\right)\right) l\left(\{0\}^*\right). \end{aligned} \tag{6}$$

Finally, we obtain a parameter called the sum of mean lengths (SML), which measures the complexity of the signal:

$$\text{SML} = L_0 + L_1. \tag{7}$$

The SML parameter is the sum of the mean values and, as such, is an average measure. However, unlike entropy per symbol, it is not a measure that directly characterizes the source of the signal but rather a measure of the complexity of the signal itself and, indirectly, its source.

In addition to providing overall signal characteristics, this parameter can be used to track the evolution of signal complexity, e.g., using the moving window technique.

3.4. *Empirical mode decomposition*

EMD decomposes multi-component signals into their mono-components, as proposed by Huang *et al.* (1998). EMD is a data-driven algorithm that does not depend on any predefined basis function. Such mono-components are called intrinsic mode functions (IMFs). An IMF is a signal that fulfills the following conditions: the number of extrema and the number of zero crossings of the IMF are either the same or their difference is 1; the signal has "zero mean" – meaning the mean value of the envelope determined by the maxima and the envelope defined by the minima is equal to 0 at every point.

The above conditions suggest that EMD – non-stationary signal is decomposed into stationary, symmetric signals (modes) that are easy to analyze.

The crucial step of EMD is extracting extrema from the original signal $x(t)$ end creating the upper envelope $e_{\max}$ and the lower envelope $e_{\min}$ by cubic spline interpolation (de Boor, 1978) of the maxima and minima, respectively. Then, the mean value of the two envelopes is computed as:

$$m(t) = \frac{e_{\max} - e_{\min}}{2}. \tag{8}$$

The value $m(t)$ is subtracted from the primary signal $x(t)$ resulting in:

$$\mathrm{imf}_1(t) = x(t) - m(t). \tag{9}$$

This is called the sifting process (Fig. 1).

In an ideal case, $\mathrm{imf}_1(t)$ could be the first mode IMF_1, but it usually remains an asymmetric signal. In such a case, we need to repeat the above procedure, treating $\mathrm{imf}_1(t)$ as the input data for the subsequent sifting process, so the mean value $m(t)$ of the envelopes of $\mathrm{imf}_1(t)$ is calculated, and this value is subtracted from $\mathrm{imf}_1(t)$:

$$\mathrm{imf}_1(t) := \mathrm{imf}_1(t) - m(t). \tag{10}$$

In Eq. (10), the sign ":=" denotes "becomes," that is, in the programming loop, the right-hand side is substituted for the left-hand side. This procedure is repeated until $\mathrm{imf}_1(t)$ meets the conditions of an IMF signal

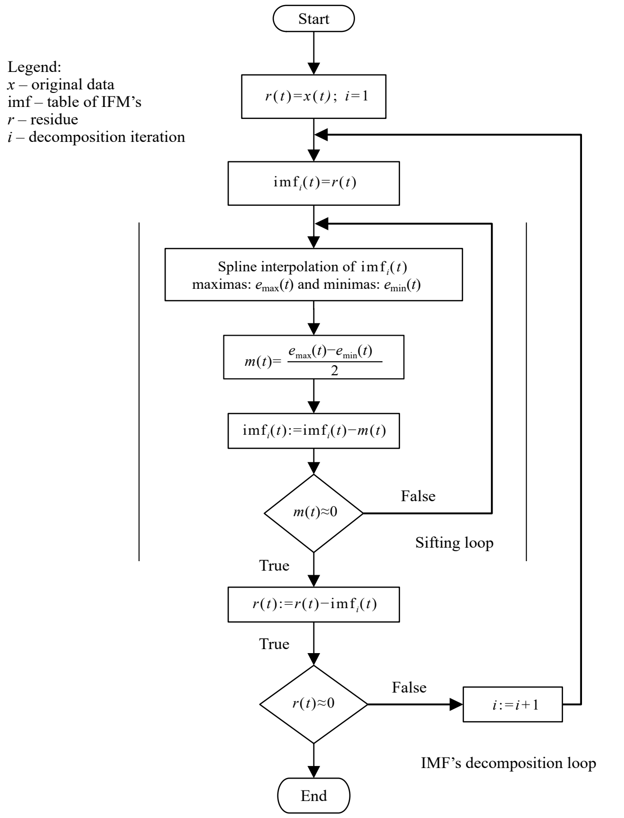


Fig. 1. Block diagram of sifting process (from (Pierzchalski *et al.*, 2011)).

($m(t) \approx 0$). After the extraction of IMF_1, the original data is reduced by the ultimate value of $\mathrm{imf}_1(t)$:

$$r(t) = x(t) - \mathrm{imf}_1(t). \tag{11}$$

The residue $r(t)$ is treated as input for extracting the subsequent IMF (next sifting loop).

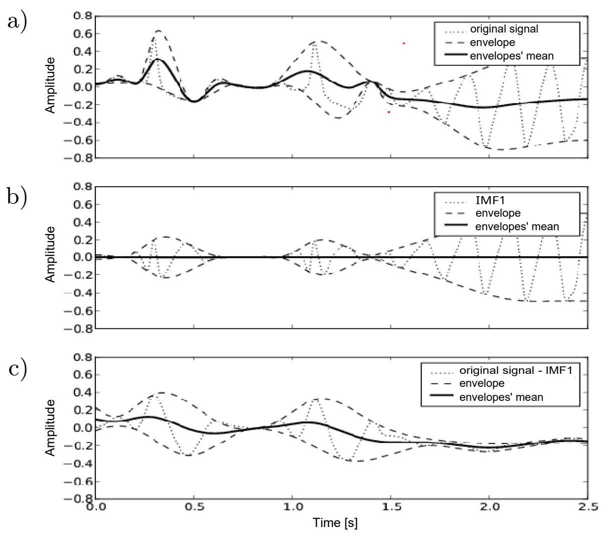


Fig. 2. EMD decomposition: a) start; b) end of the decomposition of the first IMF; c) start of the decomposition for the second IMF (from (Pierzchalski *et al.*, 2011)).

The procedure is looped to obtain all IMFs (Figs. 1 and 2). Decomposition is finished when either the i-th residue $r_i(t) = r_{i-1}(t) - \text{imf}_i(t)$ has less than three extrema or all its points are equal to zero.

The sum of all IMF components (modes) and the residue is equal to the original signal:

$$r_n + \sum_{m=1}^{n} \text{IMF}_m(t) = x(t), \tag{12}$$

where n is the number of modes.

In most analyzes using EMD, researchers focus on the modes themselves, ignoring the residue, which for many complex signals, has tiny amplitudes. However, in this study, the amplitudes of the residues are much higher than the amplitudes of the modes. Thus, the residues give the most crucial information about the signal.

4. Results

The results presented here are for five guitars that underwent the humidification process for nearly a week. The guitar designations are random and do not refer to any specific type or model of guitar. The analyzed data were obtained using the measurement and processing methods described in (Wrzeciono *et al.*, 2018).

4.1. Analysis of sound level during sustain by Higuchi's fractal dimension

Table 1 shows the derived fractal dimension values for the instruments before and after moisturizing. All tested guitars exhibited a higher fractal dimension after the humidification process than before. This means that the SPL curve for the instrument after humidification is more complex than before.

Table 1. HDF for five guitars before and after humidification.

The guitar ID	Before moisturizing	After moisturizing
110	2.12	2.18
111	2.08	2.17
112	2.01	2.2
113	2.08	2.12
114	2.19	2.22

It should be noted that the levels of fractal dimension values attained by guitars depend not only on their initial condition but also on individual features of their construction. For example, the fractal dimension value for guitar 110 before humidification is the same as for the fractal dimension of guitar 113 after humidification. However, after humidification, the fractal dimension for guitar 110 reaches the level of this value for guitar 114.

Moreover, it is observed that the level of increment in fractal dimension depends on the guitar's starting condition and susceptibility to moisturizing. The most significant increases in fractal dimension occurred for guitars 112 and 111, while for guitars 113 and 114, the increment was the smallest.

It is also intriguing that the fractal dimension values exceed the value of 2. This is probably due to the properties of the curve of the sound level during sustain, where a strong nonlinear trend is superimposed on a rapidly varying oscillation. This trend is essential in interpreting how we hear the guitar sound. We write about this further in the results section on EMD analysis.

4.2. Symbolic analysis of sustain curve

The sum of the means lengths of mono-sequences (SML), similarly to HFD, records the difference before and after conditioning the instrument (Fig. 3). For this parameter, we observe a decrease in value after conditioning. This means that the amplitudes of the fast oscillations are statistically shorter and become more uniform after humidification. The complexity of sustain curves grows after moisturizing, which agrees with the results obtained with HFD.

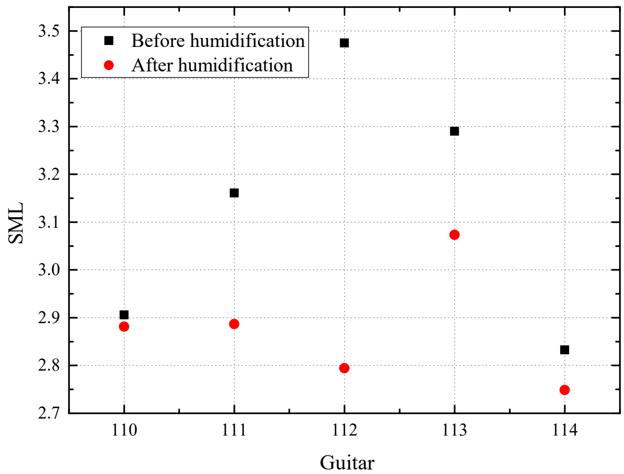


Fig. 3. Values of SML score for five instruments.

Using SML, we tracked the changes in guitars during the humidification process. Figure 4 shows the evolution of the SML scores for guitars from the first before conditioning to the last after an entire humidification cycle.

The effect of the instrument humidification process is irregular – improvement is followed by deterioration. This agrees with listening observations. The evolution during conditioning resembles a fading oscillation, indicating that guitars are moving towards their characteristic equilibrium points.

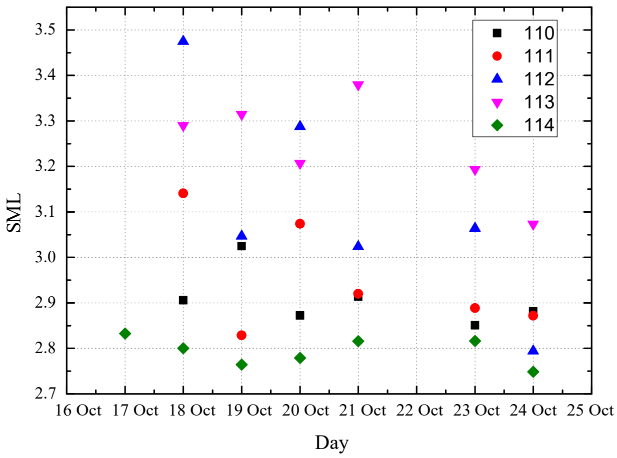


Fig. 4. Evolution of SML scores during instrument humidification.

4.3. EMD decomposition of the sound level in sustain

EMD decomposed the sound level during sustain of the guitar before and during the moisturizing procedure. Figure 5 presents the decomposition of the SPL curve for guitar 112 before and after the complete cycle of moisturizing.

For guitar 112, the number of modes did not change. However, evident changes can be seen in the shape of the mode waveforms. Here, the shape of the sustain signal is mainly affected by mode IMF_5. The bulges observed in the sustain signal of the guitar before the humidification process, audible as long ripples of sound, are associated with mode IMF_5.

In the seven decompositions, the final number of modes was five; in two cases, it was six, and in one case, it was four. Thus, for two guitars, after conditioning, the number of modes increased from five to six (guitar 111) and four to five (guitar 113, see Fig. 6); for one guitar, it decreased from six to five (guitar 114).

Especially interesting are the results of the residue decomposition of the signal. For example, residues of SPL measurements before and after humidification for guitar 110 are presented in Fig. 7.

Figure 8 shows the changes in the shapes of the residue curves determined for the instruments during the humidification process.

The shape of these curves matches the listening experience and confirms the irregular changes in instrument sound quality during humidification. In addition, an identical irregularity was observed for the previously determined SML parameter.

Through our investigation, we observed significant alterations in the playability of instruments following the humidification process, as indicated by all the methods employed.

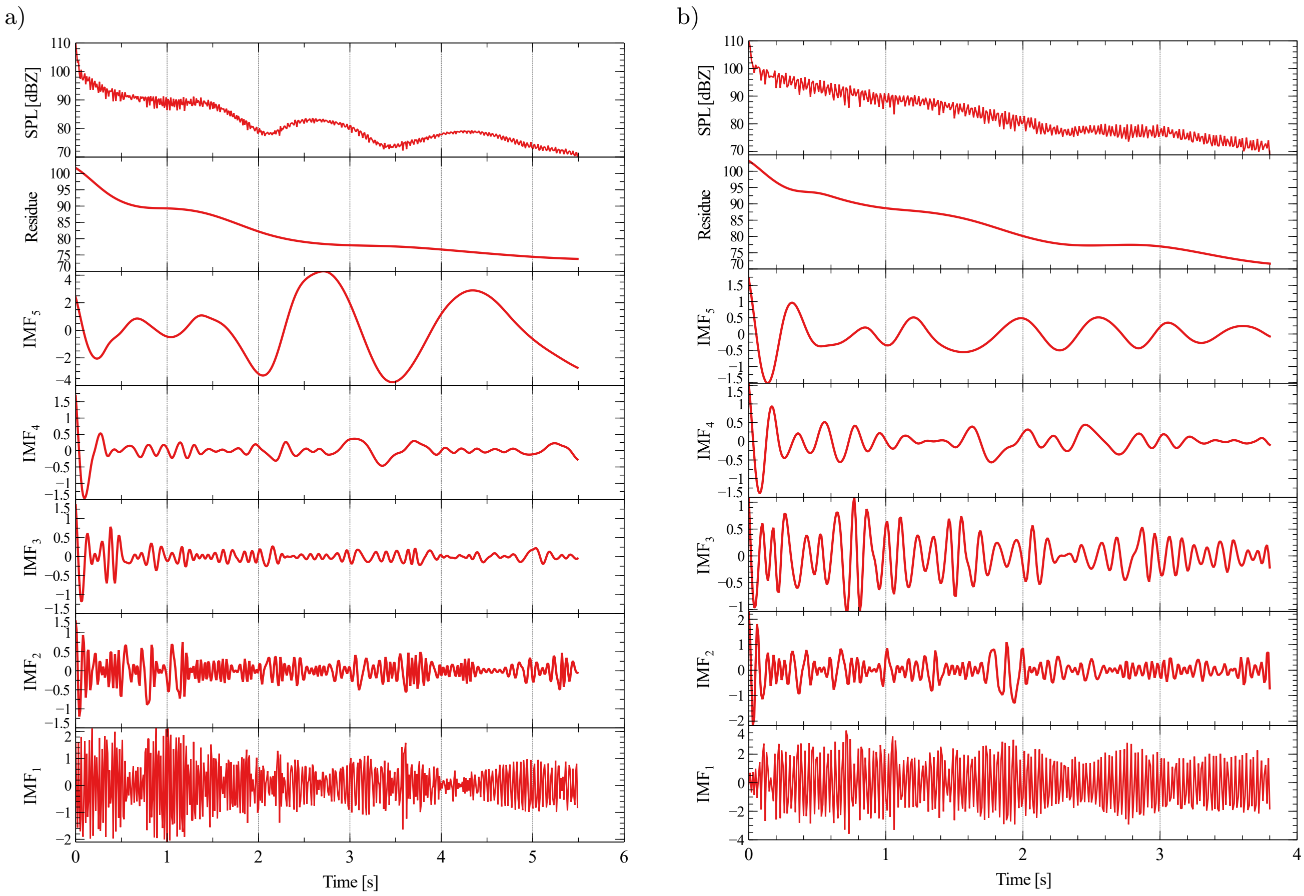


Fig. 5. EMD decomposition of the SPL for guitar 112: a) before moisturizing; b) after moisturizing.

a) b)

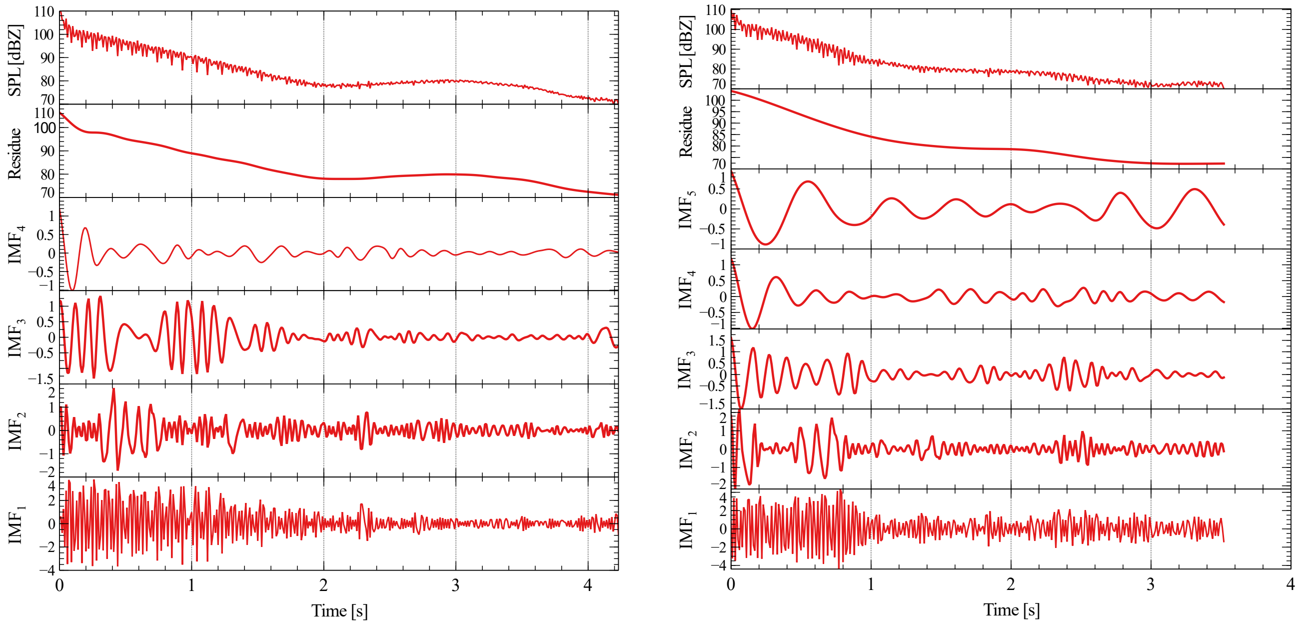


Fig. 6. EMD decomposition of the SPL for guitar 113: a) before moisturizing; b) after moisturizing.

a) b)

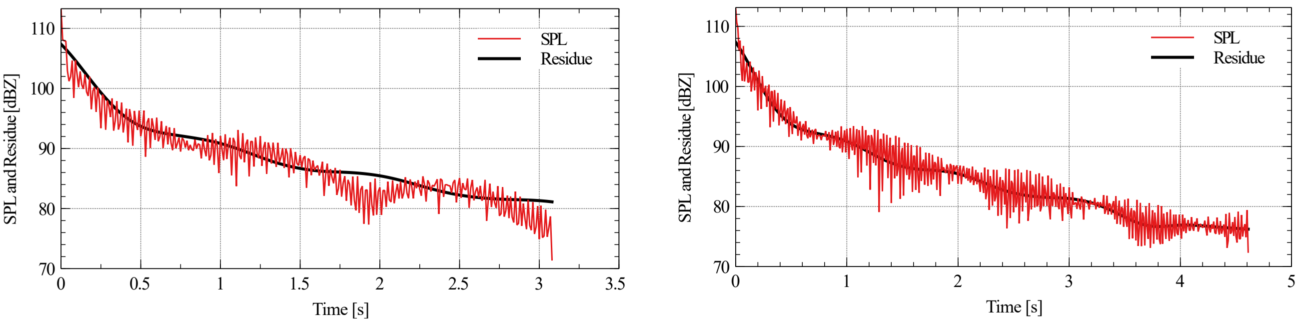
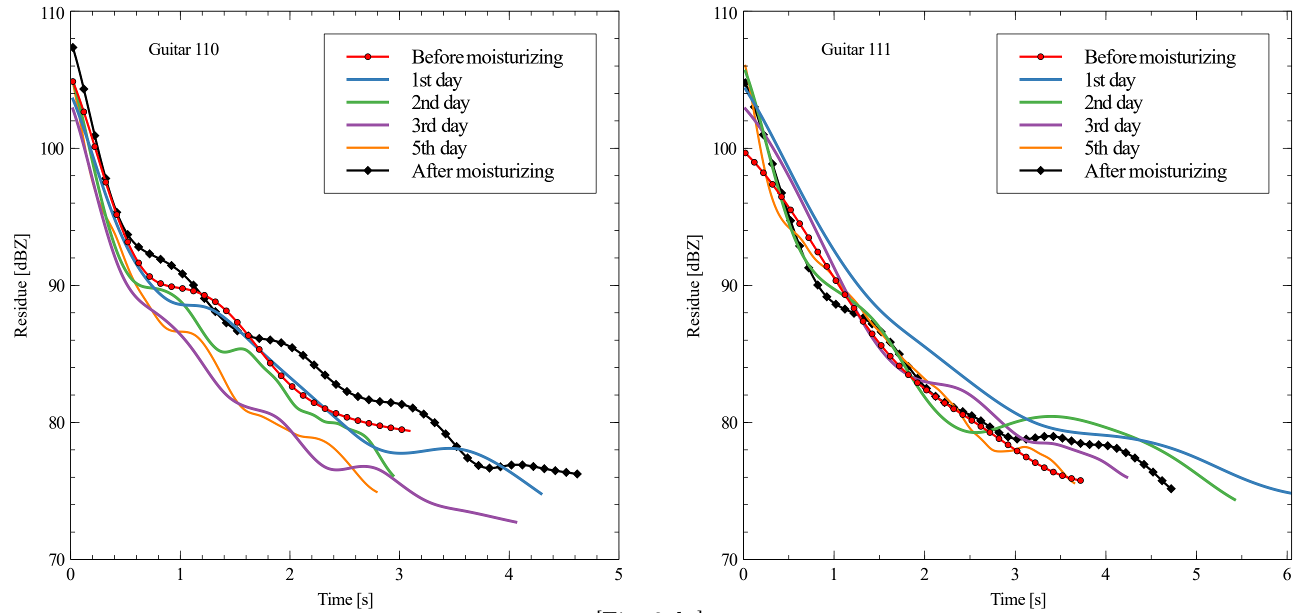


Fig. 7. Residues and sustain of 110 guitar (a) before moisturizing and (b) after moisturizing.

a) b)



[Fig. 8ab.]

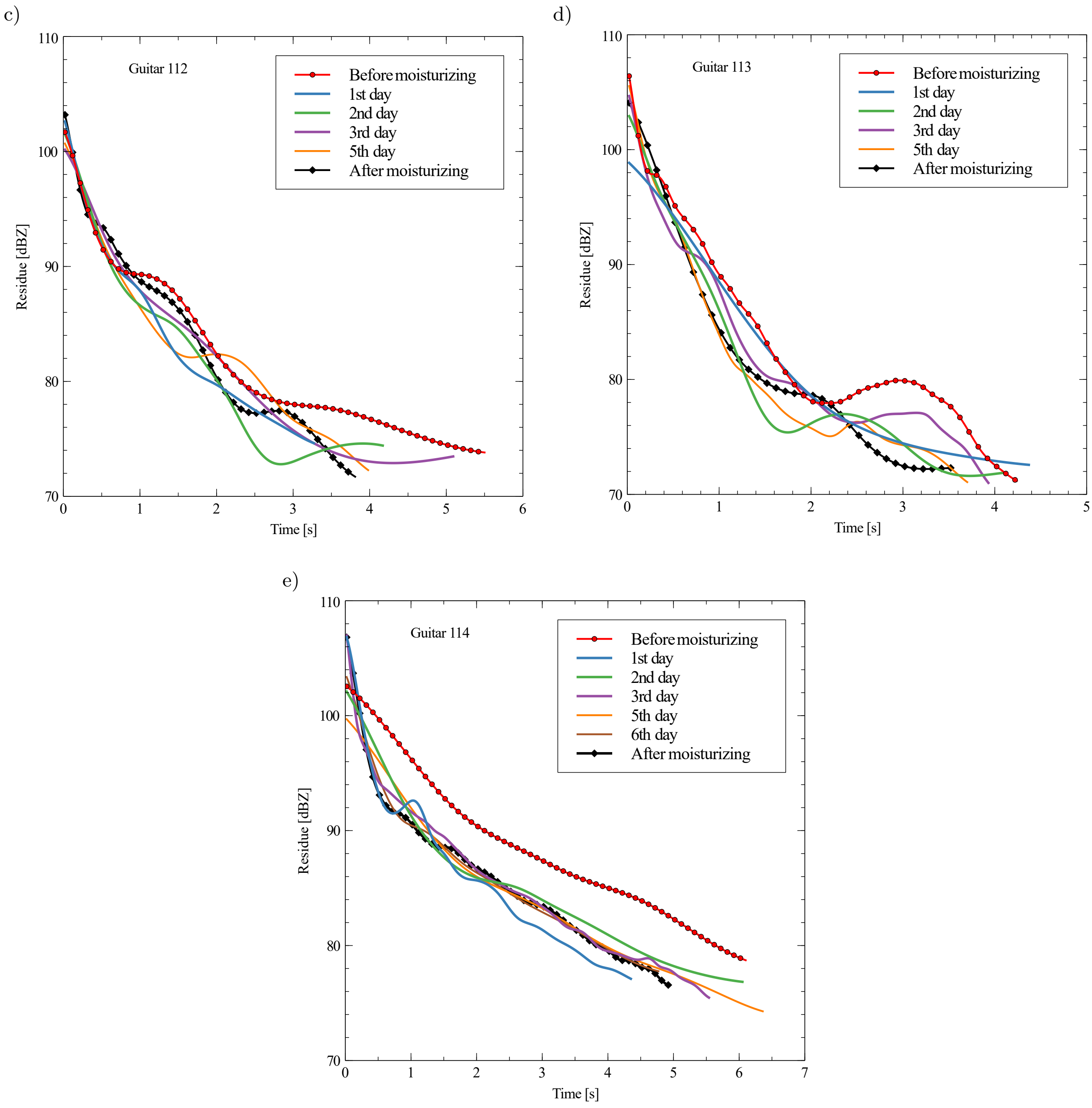


Fig. 8. Residues after the EMD decomposition of SPL measured during moisturizing procedure. The first and last measures are curves with dots.

Previously, a solution to the problem of objective assessment of the influence of the humidification procedure on guitar sound quality was proposed together with the original measurement procedure by Wrzeciono *et al.* (2018). Despite having an effective measurement method, the problem turned out to be nontrivial, and the methods of sound level analysis proposed in (Wrzeciono *et al.*, 2018) did not yield entirely satisfactory results. As a result, only the sustain time parameter T_{40} was suitable for guitar condition evaluation. Unfortunately, the disadvantage of this parameter is its excessive sensitivity to changes in the signal level cut-off moment. Therefore, in this work, more global methods that use all measured points on the sound level curve, or as in the case of EMD, generate curves containing deeper information, were used to evaluate sound level changes.

5. Conclusion

The purpose of this study was to find parameters for evaluating guitar humidification performance, and we found that complexity parameters like HFD, symbolic analysis, and EMD provide a consistent and clear depiction of the changes in guitar sound quality during the humidification process. To the best of the authors' knowledge, this is probably the first application of these methods to evaluate guitar humidification performance.

References

1. de Boor C. (1978), *A Practical Guide to Splines*, Springer-Verlag, New York.
2. Gladun K.V. (2020), Higuchi fractal dimension as a method for assessing response to sound stimuli in patients with diffuse axonal brain injury, *Modern Technologies in Medicine*, **12**(4): 63–70, doi: 10.17691/stm2020.12.4.08.
3. Gomolka R.S., Kampusch S., Kaniusas E., Thürk F., Széles J.C., Klonowski W. (2018), Higuchi fractal dimension of heart rate variability during percutaneous auricular vagus nerve stimulation in healthy and diabetic subjects, *Frontiers in Physiology*, **9**: 1162, doi: 10.3389/fphys.2018.01162.
4. Gordobil O., Herrera R., Poohphajai F., Sandak J., Sandak A. (2021), Impact of drying process on kraft lignin: Lignin-water interaction mechanism study by 2D NIR correlation spectroscopy, *Journal of Materials Research and Technology*, **12**: 159–169, doi: 10.1016/j.jmrt.2021.02.080.
5. Gore T. (2011), Wood for guitars, [in:] *Proceedings of Meetings on Acoustics 161ASA*, **12**(1): 035001.
6. Higuchi T. (1988), Approach to an irregular time series on the basis of the fractal theory, *Physica D: Nonlinear Phenomena*, **31**(2): 277–283, doi: 10.1016/0167-2789(88)90081-4.
7. Huang N.E. *et al.* (1998), The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis, *Proceedings of the Royal Society of London. Series A: Mathematical, Physical and Engineering Sciences*, **454**(1971): 903–995, doi: 10.1098/rspa.1998.0193.
8. Huang N.E., Wu Z. (2008), A review on Hilbert-Huang transform: Method and its applications to geophysical studies, *Reviews of Geophysics*, **46**(2), doi: 10.1029/2007RG000228.
9. Johnson Jr P.D., Harris G.A., Hankerson D. (2003), *Introduction to Information Theory and Data Compression*, 2nd ed., CRC.
10. Khan S.I., Pachori R.B. (2021), Automated classification of lung sound signals based on empirical mode decomposition, *Expert Systems with Applications*, **184**: 115456, doi: 10.1016/j.eswa.2021.115456.
11. Li C. *et al.* (2021), Seizure onset detection using empirical mode decomposition and common spatial pattern, [in:] *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, **29**: 458–467, doi: 10.1109/TNSRE.2021.3055276.
12. Mandelbrot B. (1967), How long is the coast of Britain? Statistical self-similarity and fractional dimension, *Science*, **156**(3775): 636–638.
13. Pierzchalski M., Stepien R.A., Stepien P. (2011), New nonlinear methods of heart rate variability analysis in diagnostics of atrial fibrillation, *International Journal of Biology and Biomedical Engineering*, **5**(4): 201–208.
14. Rath J., Staudinger G. (2001), Cracking reactions of tar from pyrolysis of spruce wood, *Fuel*, **80**(10): 1379–1389, doi: 10.1016/S0016-2361(01)00016-3.
15. Ribeiro H.V., Jauregui M., Zunino L., Lenzi E.K. (2017), Characterizing time series via complexity-entropy curves, *Physical Review E*, **95**(6): 062106, doi: 10.1103/PhysRevE.95.062106.
16. Ribeiro H.V., Zunino L., Mendes R.S., Lenzi E.K. (2012), Complexity-entropy causality plane: A useful approach for distinguishing songs, *Physica A: Statistical Mechanics and its Applications*, **391**(7): 2421–2428, doi: 10.1016/j.physa.2011.12.009.
17. Spasić S., Kalauzi A., Ćulić M., Grbić G., Martać L. (2005), Estimation of parameter $k_{\max}$ in fractal analysis of rat brain activity, *Annals of the New York Academy of Sciences*, **1048**(1): 427–429, doi: 10.1196/annals.1342.054.
18. Stepien R.A. (2011), New method for analysis of nonstationary signals, *Nonlinear Biomedical Physics*, **5**(1): 1–8, doi: 10.1186/1753-4631-5-3.
19. Stojadinović G. *et al.* (2020). The effects of Nembutal on the intracerebellar EEG activity revealed by spectral and fractal analysis, *Archives of Biological Sciences*, **72**(3): 425–432.
20. Stone J.V. (2022), *Information Theory: A Tutorial Introduction*, 2nd ed., Sebtel Press.
21. Wrzeciono P., Przybylski W., Ostrowski A. (2018), Guitar Sound Parameters to assess the impact of atmospheric conditions on the acoustic qualities of the instrument, [in:] *2018 Joint Conference – Acoustics*, pp. 1–5, doi: 10.1109/ACOUSTICS.2018.8502376.
22. Zheng J., Su M., Ying W., Tong J., Pan Z. (2021), Improved uniform phase empirical mode decomposition and its application in machinery fault diagnosis, *Measurement*, **179**: 109425, doi: 10.1016/j.measurement.2021.109425.
23. Zhou S., Bethel B.J., Sun W., Zhao Y., Xie W., Dong C. (2021), Improving significant wave height forecasts using a joint empirical mode decomposition–long short-term memory network, *Journal of Marine Science and Engineering*, **9**(7): 744, doi: 10.3390/jmse9070744.