Features vs Bands: Statistical analysis between design features and spectral power for a set of culturally relevant violins

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***Abstract*—This study presents a comprehensive statistical analysis exploring the relationship between the design parameters and the power of the sound spectrum of culturally significant violins. Our research aims to quantitatively correlate physical design elements with acoustic output in two different representations: modal features and octave-band averages of the sound pressure level. Key design parameters, such as body shape and wood properties, were systematically documented. The statistical analysis focused on identifying patterns and correlations between the physical characteristics of the violins and their spectral power distributions. Our findings reveal intriguing connections between certain design parameters and specific aspects of the violins' acoustic output. These insights not only contribute to a deeper understanding of the acoustic impact of violin craftsmanship but also bridge the gap between traditional artisanship and scientific inquiry. The study's implications extend to violin makers, performers, and historians, offering a novel perspective on the interplay between design, culture, and acoustics in these instruments.**

***Index Terms*—Acoustics, Audio Signal Processing, Musical Signal Processing**

I. INTRODUCTION

Understanding what makes a violin great has eluded science for hundreds of years. There is a complete mythology developed around it, and people tend to search for the "secret" of the old masters [1]. Perhaps the largest limitation to a proper study of the violin lays in both its constitutive materials and the time and craft needed to create this instrument. Experiments done in the scientific world are always severely limited in their numbers [2], and the intrinsic variation of wood [3] makes conclusions not insightful. Without a carefully controlled selection of the material, and the same level of control in the construction of the instrument, these experiments cannot see beyond the noise of material variability.

Our approach is rather different. By using data collected through a 20-years trajectory, and inspired by data science [4], we are able to take advantage of the large number of samples to overcome these challenges and obtain robust, significant correlations between the constructive parameters and vibrational response of the instrument, and the subjective evaluation of those instrument by professional players.

In particular, in this article we focus on what is the best way to represent the sound radiation of an instrument. To achieve this, we study the correlation between the construction parameters and different features of the measured sound: power per bands, and modal/statistical features of the Sound Pressure Level (SPL). The aim of either representations is the same, i.e. to transform a continuous signal into a set of discrete dimensions, lowering greatly the dimensionality of the data under study and allowing one to understand how to control the acoustic response of the violin.

II. MATERIALS AND METHODS

A. Violins

Our dataset consists of 55 instruments made by the same maker, Sam Zygmuntowicz, during his 20-plus years of professional career, and are mostly owned by professional players active in the cultural field. This dataset represents a

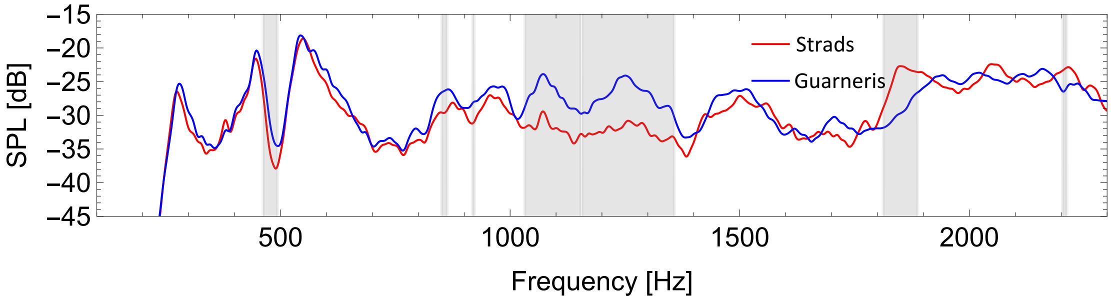

Fig. 1. Average SPL, as a function of frequency, for the two different models of the dataset: Stradivari models (red) and Guarneri models (blue).

unique opportunity in the world of violin making to study, scientifically, the output of one maker for whose instruments there is a systematic record of their construction parameters.

The dataset includes two different models, Stradivaris and Guarneris (also known as Del Gesú), the former with 21 samples and the second with 34. For the ease of readability, we will refer to the two models with the terms “Strads” and “Guarneris”, respectively.

The preliminary study showed certain differences between the models, so we have decided to split the dataset in two. The averaged SPL for the two datasets is shown in Fig. 1. The frequency regions where the difference between them is larger than 3 dB has been highlighted.

B. Radiation measurements

The radiation measurements were performed by means of hammer impact testing. A structure made of wood and rubber bands was built to approximate free boundary conditions during the test. Four rubber bands were used for the suspension of the instrument, letting the sample in vertical position and minimizing the contact surface [5], [6]. In particular, two rubber bands were placed at the bottom of the violin while the remaining two supported its soundbox from the upper corners. In this configuration, also the resting position of the hammer results vertical after the hit, avoiding the occurrence of accidental secondary strikes during the acquisition.

A dynamometric hammer with light tip (086E80, by *PCB Piezotronics*) and a Behringer ECM8000 microphone, 30 cm far from the axis of rotation and pointing at the bridge, were used to generate an impulsive excitation and measure the violin response in terms of radiated sound pressure, respectively. Impacts were applied on one edge of the bridge. For each measurement, six time-domain signals of two seconds sampled at 48 kHz were acquired per position: instrument front, 30° toward bar, 30° toward post, and back. Frequency Response Functions (FRFs) were then estimated following the definition of the H1 estimator to reduce noise caused by the instrumentation [7]. The magnitude of the resulting FRFs are represented in dB scale and averaged across all the positions. We call this radiation measurement of the SPL.

The spatial and per bin average is computed in dB scale to be consistent with the standard used in the violin making community [1].

C. Frequency bands analysis

Since the SPL is a multidimensional object, it is cumbersome to work with the raw data. Because of this, we divide the SPL in bands, each band indexed by j, and average the frequency-dependent SPL values $P(\omega)$ over all the frequencies in that band. Therefore, the band-averaged SPL for the i-th violin is

$$P_{i,j} = \frac{1}{N_j}\sum_{k=1}^{N_j} P_i(\omega_{k,j}) \ , \tag{1}$$

where N_j is the number of frequency bins included in the j-th band, and $\omega_{1,j}, \omega_{N_j,j}$ are the first and last frequency bins in the band, respectively. For our studies, we use integer subdivisions of octave bands centred at multiples of the fundamental A at 440 Hz, such that there are 3 bands between two octaves.

By taking the average over all the N_i violins in the dataset, namely

$$\bar{P}_j = \frac{1}{N_i}\sum_{i=1}^{N_i} P_{i,j} \ , \tag{2}$$

The band-averaged SPL of an individual violin can thus be re-written as variations of the SPL around the average as

$$P_{i,j} = \bar{P}_j + \delta P_{i,j} \ . \tag{3}$$

Let the vector of $m = 37$ design parameters, i.e. construction and material parameters, be $\mathbf{F}_i \in \mathbb{R}^m$ for each violin. We assume that a linear model explains the relationship between SPL and design parameters. Our hypothesis thus reads in matrix form as

$$\begin{bmatrix} \delta P_{1,j} \\ \vdots \\ \delta P_{N_i,j} \end{bmatrix} = \mathbf{M}_j^T \cdot \mathbf{F}_i \quad \forall j \ , \tag{4}$$

where $\mathbf{M}_j$ is a matrix of $(m \times N_i)$ linear coefficients. In order to solve the linear system and find $\mathbf{M}_j$, we need at least to have more instruments than design parameter variations, otherwise the system is overdetermined.

For the sake of simplicity though, instead of solving the least-squares problem of fitting the design parameters to the

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[1] https://sites.google.com/view/oberlinacoustics/home

radiated sound, as a first step in this article we will focus on the linear correlation between each of the construction parameters and the SPL, both in its band and feature-based representation.

D. *Feature-based Representation*

Another option to describe the SPL is to extract acoustic features from the frequency-dependent SPL function, as we have done previously to study the mobility of a set of violins [8]. Contrary to the mobility, which is measured as the vibrational response of the instrument to an impulse, the SPL is measured as an average of radiated power at different locations with respect to the instrument.

Instead of looking at the power per band in the SPL signal, we define a set of hand-crafted acoustic "features" that coarsely describe the SPL in the low and high frequency regions. These features are computed by analysing the modal characteristics of the first four peaks in the SPL, the behaviour in the mid range of the instrument via the integrated Relative Power (RP) [9], and the slope of the SPL from 4000 Hz onwards. For the sake of space, we only give a summary table of the features as they have been defined previously [8].

Figure 2 shows some of these features for the two datasets of violins, Stradivari and Guarneri models. In particular, the frequencies, amplitudes, and Q-factors of the first four body modes are reported. As it can be seen, there is no statistically significant difference between one dataset and the other, just as highlighted by the SPL plot of the averages in Fig. 1.

Name	**Description**
Signature mode frequencies	
f_1	Frequency of the first signature mode (A0)
f_2	Frequency of the second signature mode (CBR)
f_3	Frequency of the third signature mode (B1-)
f_4	Frequency of the fourth signature mode (B1+)
Signature mode amplitudes	
p_1	Amplitude of the first signature mode (A0)
p_2	Amplitude of the second signature mode (CBR)
p_3	Amplitude of the third signature mode (B1-)
p_4	Amplitude of the fourth signature mode (B1+)
Signature mode damping	
q_1	Q-factor of the first signature mode (A0)
q_2	Q-factor of the second signature mode (CBR)
q_3	Q-factor of the third signature mode (B1-)
q_4	Q-factor of the fourth signature mode (B1+)
Mid-frequency	
ω_{mid}	Frequency of the first antiresonance after mode B1+
RP_{mid}	Relative Power of the signature modes, $RP_{mid} = RP(\omega_{mid})$
ω^*	Sigmoid center frequency
RP^*	Relative Power center value, $RP^* = RP(\omega^*)$
k^*	Relative Power curvature
ΔA	Area difference, $\Delta A = MSE(RP(\omega), \sigma'(\omega, \omega_{mid}, \omega^*, k^*))$
k_{high}	Slope of the linear fit at high frequency

TABLE I
SUMMARY OF THE LOW AND MID-FREQUENCY FEATURES DEFINED.

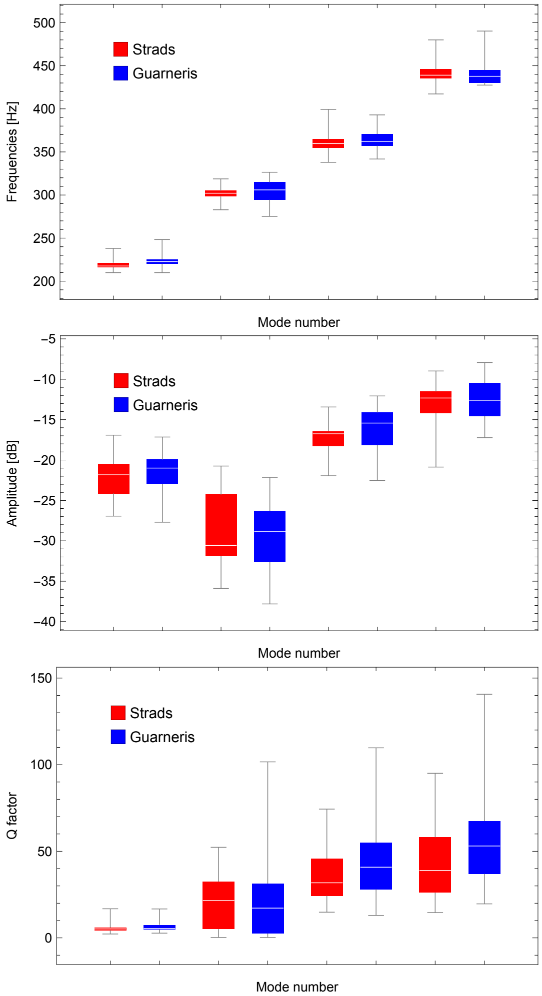

Fig. 2. Modal features for the two datasets of violins, Stradivari (red) and Guarneri (blue) models. **Top**: frequency of the first body modes. **Centre**: SPL amplitude at those frequencies. **Bottom**: Q-factor associated to the four peaks. As it can be seen, there is no statistically significant difference between the two datasets.

III. RESULTS

For the sake of brevity, in what follows we will focus on the dataset of the Stradivari models, as they exhibit a more standard behavior than the Guarneri ones. Indeed, the Guarneris present a more varied collection of shape models, i.e. 8 versus 5.

Figure 3 left shows the coefficient of determination R^2 between the design parameters of the violins (1-37) and the SPL in third of octave bands for the Stradivari models dataset. The computation of the R^2 coefficient is based on the definition of the Pearson correlation coefficient [10]. Interestingly, it seems that there are 3 regions of different correlation. The low region, where the SPL is strongly correlated with a few parameters, the middle region where the SPL has a general low correlation with everything, and the high range where the SPL correlates strongly with more variables than the low range, in a manner that is rather consistent for various frequencies. This seems to agree with what makers think, i.e. that different

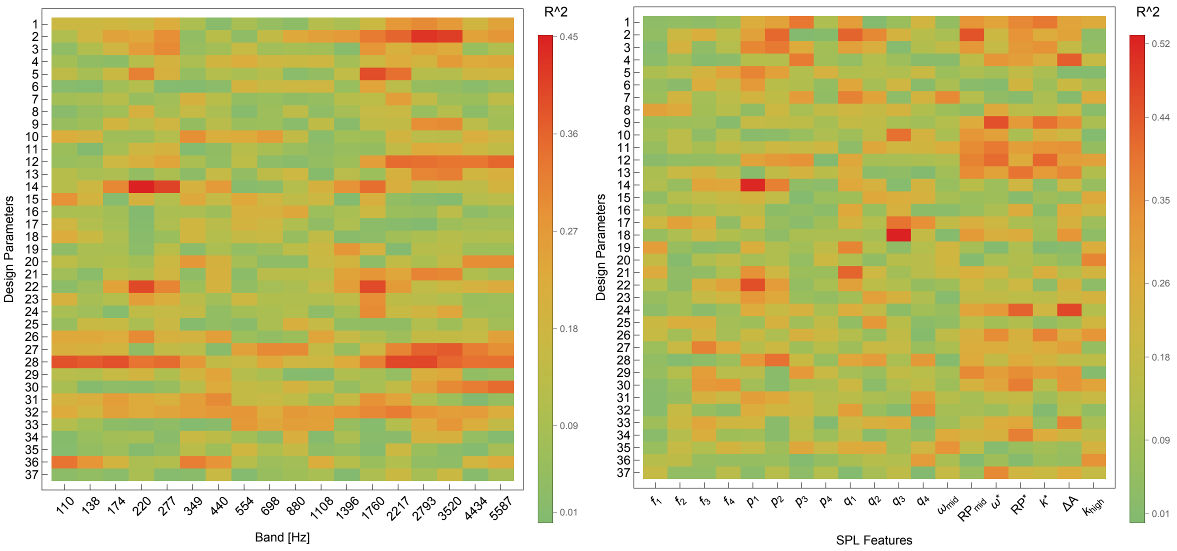

Fig. 3. Coefficient of determination R^2 between the two proposed representations of the SPL and the design parameters of the instrument. **Left:** Comparison with band-averaged SPL. **Right:** Comparison with feature-based SPL.

design parameters have different roles and impact in different regions of the instrument sound. For example, the size of the instrument determines the low range response, whereas the material properties of the wood (density and stiffness) are more related to the high end of the response.

Figure 3 right shows the same R^2 matrix but this time when looking at the modal features of the SPL rather than to the band average. The correlation between some of the SPL features and the parameters is larger than for the SPL bands, but in general it shows a slightly higher correlation than band averaging. Interesting, and contrary to much of the literature discussion on how the design parameters affect the "signature modes" [11], there seems to be no correlation between the design parameters and the frequency of these modes for this dataset. Since this is a real world example of how instruments are built, and the range of values in which these parameters are moved, we do not see the point why these features should still be considered as relevant for the description of the instrument when they clearly cannot distinguish statistically between two different models.

Interestingly, all the construction variables (Design Parameters in Fig. 3) correspond to free plates variables. Amongst the most relevant ones, we can find the top plate density (2), top plate mass (14), height of the bass-bar (28) and top mode 5 frequency (15). These variables are either directly controlled by the maker by selecting the wood or doing some treatments to it [12], [13] or instead, can be predicted from the geometric and material parameters of the plate, as the frequency of mode 5 [4]. All this shows that, in fact, violin making can in principle be transformed in something more akin to a science, where objective recipes and range of values determine the radiative response of the instrument. How that relates to the perceived quality of the instrument remains an open question though.

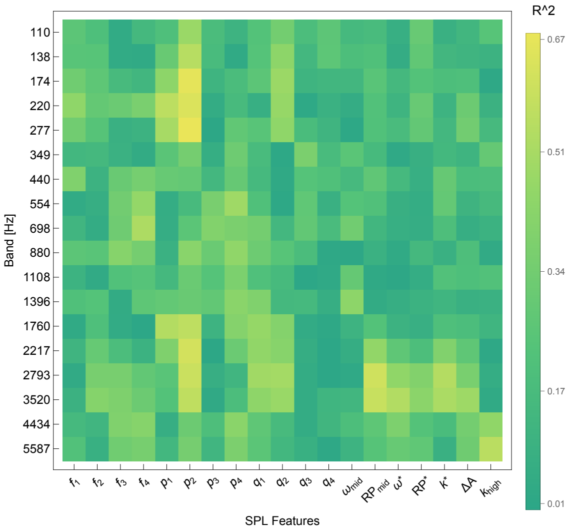

Fig. 4. Coefficient of determination R^2 between modal features and band averages for third of octave bands.

Finally, to show how complementary the two representations are, Fig. 4 shows that the coefficient of determination between the two representations is quite low, with only 9 variables of the feature dataset showing a correlation coefficient larger than 0.5 with the band averaged SPL. As expected, the power of the peaks p_i, shows the largest correlation with the averaged SPL, as well as the slope variable k_{high}.

IV. CONCLUSIONS

In this article, we have studied the largest corpus of violins for a single maker using design parameters and radiation data of violins spanning 20 years of career. We have studied the radiation under two different yet related representations: the band average of the power spectra, and the modal parameters for the low modes together with statistical descriptors of the mid- and high-range frequency response. We have found that a mix of both representations can be useful, and each representation correlates with different design parameters.

These results are coherent with previous results from simulations [4], [14]–[16] and demonstrate that free plate features can be used to predict part of the complete instrument's behaviour. A caveat of the results presented here is that we are using the simplest possible linear correlation between design parameters and radiation measurements. It stands to reason that some variables may have a quadratic dependence instead or other kind of non-linearities. Recent advances in neural networks applied to material characterisation and sound prediction of complete instruments [17]–[19] indicate that similar approaches could be used here, albeit the amount of data of this particular dataset is not enough to train even the simplest of the neural network architectures.

One of the relevant aspects presented in this article is the fact that, contrary to the lore of violin making research, different violin models do not statistically differentiate in the signature modes of the instrument. If there is any difference that can be associated to the different models, is definitely not where the state of the art have been looking for them. Finding what are the spectral features that best differentiate instruments is beyond the scope of this article, but something that could only be achieved with datasets like the ones presented here. It seems clear to us that there are just two possibilities: either the violins are different in other, higher frequency spectral features, or they are statistically the same regardless of the model. Either way the current understanding of the role of signature modes in the sound of an instrument needs to be updated at best, and completely disregarded at worst.

The question of how these spectral features correlate with the perceived sound of an instrument is still an open one, but one in which digital experimentation has a lot to say [20]. The results presented here demonstrate that there are indeed correlations between design and radiated sound features, albeit very weak ones. Reasons for this include the fact that this is not an experimental set up but real data from a commercially successful maker, and as such the violins need to fulfil criteria beyond mere accuracy and reproducibility. Furthermore, there are several non-recorded variables in the construction process, in particular information about the arching of the instruments, which become highly relevant when all the other variables are as controlled as they are in this set of instruments.

Eventually, once we know how the spectral features determine perception, we will be able to design instruments for a desired timbral response. The results presented here are a necessary step to achieve that.

REFERENCES

[1] S. F. Sacconi, "The" secrets" of stradivari: with the catalogue of the stradivarian relics contained in the civic museum" ala ponzone" of cremona," *(No Title)*, 1979.

[2] C. Fritz, I. Cross, B. C. Moore, and J. Woodhouse, "Perceptual thresholds for detecting modifications applied to the acoustical properties of a violin," *The Journal of the Acoustical Society of America*, vol. 122, no. 6, pp. 3640–3650, 2007.

[3] S. Merchel, M. Altinsoy, and D. Olson, "Perceptual evaluation of bracewood and soundboard wood variations on the preference of a steel-string acoustic guitar," *The Journal of the Acoustical Society of America*, vol. 146, no. 4, pp. 2608–2618, 2019.

[4] S. Gonzalez, D. Salvi, D. Baeza, F. Antonacci, and A. Sarti, "A data-driven approach to violin making," *Scientific reports*, vol. 11, no. 1, pp. 1–9, 2021.

[5] C. Vasques and J. D. Rodrigues, "Vibration and structural acoustics analysis: Current research and related technologies," 2011.

[6] T. Kiesel, P. Langer, and S. Marburg, "Numerical study on the effect of gravity on modal analysis of thin-walled structures," *Acta Acustica united with Acustica*, vol. 105, no. 3, pp. 545–554, 2019.

[7] B. J. Schwarz and M. H. Richardson, "Experimental modal analysis," *CSI Reliability week*, vol. 35, no. 1, pp. 1–12, 1999.

[8] R. Malvermi, S. Gonzalez, F. Antonacci, A. Sarti, and R. Corradi, "A statistical approach to violin evaluation," *Applied Sciences*, vol. 12, no. 14, p. 7313, 2022.

[9] R. Malvermi, S. Gonzalez, M. Quintavalla, F. Antonacci, A. Sarti, J. A. Torres, and R. Corradi, "Feature-based representation for violin bridge admittances," in *"Advances in Acoustics, Noise and Vibration - 2021" Proceedings of the 27th International Congress on Sound and Vibration, ICSV 2021*, 2021.

[10] J. Cohen, *Statistical power analysis for the behavioral sciences*. Routledge, 2013.

[11] C. Gough, "Violin plate modes," *The Journal of the Acoustical Society of America*, vol. 137, no. 1, pp. 139–153, 2015.

[12] S. Gonzalez, E. Chacra, C. Carreño, and C. Espinoza, "Wooden mechanical metamaterials: towards tunable wood plates," *Materials & Design*, vol. 221, p. 110952, 2022.

[13] R. Malvermi, M. Albano, S. Gonzalez, G. Fiocco, F. Antonacci, M. Malagodi, and A. Sarti, "The impact of alkaline treatments on elasticity in spruce tonewood," *Scientific Reports*, vol. 12, no. 1, p. 13335, 2022.

[14] S. Gonzalez, D. Salvi, F. Antonacci, and A. Sarti, "Eigenfrequency optimisation of free violin plates," *The Journal of the Acoustical Society of America*, vol. 149, no. 3, pp. 1400–1410, 2021.

[15] D. Salvi, S. Gonzalez, F. Antonacci, and A. Sarti, "Parametric optimization of violin top plates using machine learning," *27th International Congress on Sound and Vibration, ICSV 2021*, 2021.

[16] A. Brauchler, S. Gonzalez, M. Vierneisel, P. Ziegler, F. Antonacci, A. Sarti, and P. Eberhard, "Model-predicted geometry variations to compensate material variability in the design of classical guitars," *Scientific Reports*, vol. 13, no. 12766, Aug 2023.

[17] D. G. Badiane, S. Gonzalez, R. Malvermi, F. Antonacci, and A. Sarti, "On the prediction of the frequency response of a wooden plate from its mechanical parameters," in *ICASSP 2022-2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2022.

[18] G. Longo, S. Gonzalez, F. Antonacci, and A. Sarti, "Predicting the acoustics of archtop guitars using an ai-based algorithm trained on fem simulations," in *Forum Acusticum, submitted*, 2023.

[19] D. G. Badiane, S. Gonzalez, R. Malvermi, F. Antonacci, and A. Sarti, "A neural network-based method for spruce tonewood characterization," *The Journal of the Acoustical Society of America*, vol. 154, no. 2, pp. 730–738, 2023.

[20] C. Fritz, J. Woodhouse, F. P.-H. Cheng, I. Cross, A. F. Blackwell, and B. C. Moore, "Perceptual studies of violin body damping and vibrato," *The Journal of the Acoustical Society of America*, vol. 127, no. 1, pp. 513–524, 2010.