Material Selection and Tone Control Mechanism of Leather Drumheads for Percussion Instruments

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ABSTRACT This study proposes a physics-informed neural network framework for quantitative analysis of the coupling mechanism between leather drumhead material properties and radiated acoustic wave characteristics. A transversely isotropic Ogden hyperelastic constitutive model is embedded into nonlinear shell vibration equations and incorporated as a physical constraint within the learning architecture. The proposed framework jointly utilizes transient displacement fields captured through high-speed optical measurements and acoustic wave information acquired by an array-based microphone system. Through vibration–radiation coupling modeling, structural dynamic responses are linked to farfield sound pressure distributions and spectral characteristics. Higher-order statistical moments of the Mel-frequency spectrum are employed to characterize multidimensional timbre attributes, while a differentiable material-parameter layer enables end-to-end inversion from target acoustic wave features to constitutive parameters. Experimental results demonstrate relative inversion errors of 2.3%, 2.5%, and 2.0% for Young's modulus, shear modulus, and damping coefficient, respectively. The model further exhibits high consistency in acoustic feature reconstruction and superior capability in capturing high-frequency modal responses compared with conventional linear constitutive approaches. The results reveal a quantitative relationship among material nonlinearity, vibration behavior, and acoustic wave propagation characteristics. The proposed framework provides an engineering methodology for wave-based parameter identification, vibration–radiation analysis, and acoustic field prediction, supporting intelligent design and digital restoration of percussion instruments.

INDEX TERMS wave propagation, vibration-radiation coupling, microphone array, physics-informed neural network

I. INTRODUCTION

As one of the oldest sound-producing tools, the acoustic performance of percussion instruments is highly dependent on the physical properties of the diaphragm material. The unique nonlinear elasticity, anisotropic structures, and environmental sensitivity of leather drumheads make them a central component of both traditional and modern classical percussion instruments. Understanding the scientific relationship between the properties of a drumhead's material and its associated timbre is vital to preserve and advance the instrument-making skills of future generations. Additionally, this information supports development of acoustical material design, digital audio modelling, and cultural heritage restoration [1,2]. The ability to create a calculable way to link together the parameters of materials used to manufacture a drumhead with the resulting perceived timbre created by that instrument has significant engineering applications and crossdisciplinary value [3,4].

Modern drumhead vibration modeling typically utilizes linear thin-plate or thin film theory, presuming uniformity and isotropy of material components, and small deformation in size and shape. These assumptions limit accurate modeling of the effects of large deformation, hysteresis, and stress softening on natural leather when the drumhead is struck [5,6]. In terms of testing for timbre, conventional methodologies utilize modal hammer and sinusoidal sweeping to measure the response of drumheads. Neither of these methods adequately reflects the nonlinear drumhead response to broadband transient excitation [7,8]. By oversimplifying timbre to a few low-dimensional metrics, including fundamental frequency and decay time, research has overlooked the contributions to perceptual timbre from many other parameters, including spectral envelope, transient onsets, and higher-order vibrations [9,10]. Thus, the strong reliance on the artisanal experience of craftsmen for material selection is due to an absence of a rigorous quantitative model that connects microscopic characteristics with macroscopic acoustic output, and therefore lacks a clear and reliable framework for timbre control [11,12]. These limitations have resulted in the material-timbre relationship remaining at the qualitative description level, unable to support systematic and predictable instrument design and timbre shaping [13,14].

Previous studies have attempted to introduce the finite element method to simulate drumhead vibration, but precise input of material constitutive parameters is required. However, mechanical testing of natural leather suffers from problems such as large sample dispersion and sensitivity to boundary conditions, leading to significant deviations between simulation and actual measurements [15,16]. Data-driven methods such as support vector regression or shallow neural networks have been used for timbre prediction, but without embedding physical constraints, their generalization ability drops sharply when training data is insufficient, making it difficult to guide the selection of new materials. Recently, physical information neural networks have been used for acoustic inverse problems, but their application in membrane structures is still based on linear wave equations, without considering the hyperelasticity and anisotropy of leather materials, and therefore cannot effectively support timbre control of complex nonlinear systems [17,18]. These methods either ignore material nonlinearity or separate physical mechanisms from data-driven approaches, failing to achieve interpretable inversion from target timbre to material parameters, thus obscuring the key mechanisms of selection and control. Therefore, how to integrate nonlinear constitutive priors, multimodal measurement data, and high-dimensional timbre representation within a unified framework, and reveal and quantify their intrinsic mechanisms, remains an unsolved core problem [19,20].

To address the lack of a computationally achievable and inversely relevant physical mapping mechanism between the material properties of leather drumheads and their timbre, this paper constructs a physical information neural network embedded with a nonlinear shell vibration constitutive model. This method uses a transversely isotropic Ogden hyperelastic model to describe the stress-strain relationship of leather, embedding it as the physical loss term in the neural network as a constitutive constraint. The nonlinear dynamic equations of the thin shell geometry serve as the governing equations, simultaneously fitting the transient displacement field of the drumhead measured by high-speed optical methods with the sound pressure signal acquired by a microphone array. The optimization objective is created by using a timbre feature vector that is based on the Mel spectrum's higher order moments, along with a material parameter layer which allows for the direct inverse solution of those parameters through an end-user perspective. When combined with existing models and tools for scientific selection of percussion instruments' drumhead material parameters and timbral control mechanisms, this new modeling framework provides a new theoretical basis to stimulate future research into ways to understand the complex relationships between material nonlinearities, structural dynamic behavior, and sound radiation. This framework thereby elucidates the quantitative relationship through which material properties influence timbre via physical mechanisms, establishing a theoretical basis for the reverse engineering of materials to achieve specific acoustic outcomes.

II. DRUMHEAD MATERIAL – TIMBRE COUPLING MODELING METHOD

A. MODELING OF NONLINEAR VIBRATION OF DRUM SURFACE BASED ON HYPERELASTIC CONSTITUTIVE MODEL

Leather drumheads undergo large deformation, nonlinear stress response, and significant anisotropic behavior under impact excitation, and their mechanical properties cannot be accurately described by linear elasticity theory [21,22]. To establish a vibration model consistent with physical reality, this paper adopts nonlinear thin-shell theory, treating the drumhead as an initially tensioned transversely isotropic hyperelastic membrane. Let the mid-surface parameter of the drumhead be X(θ,r,t), where (r,θ) is the polar coordinate and t is time; then the Green-Lagrange strain tensor E is defined as:

$$E = \frac{1}{2}\left(\nabla u + (\nabla u)^{\top} + (\nabla u)^{\top}\nabla u\right) \tag{1}$$

Where u is the displacement field. For natural leather, its principal fiber directions are distributed radially and circumferentially, exhibiting transverse isotropic characteristics. Therefore, the constitutive relation is described using an Ogden-type hyperelastic strain energy function:

$$W = \sum_{p=1}^{N} \frac{\mu_p}{\alpha_p}\left(\lambda_1^{\alpha_p} + \lambda_2^{\alpha_p} + \lambda_3^{\alpha_p} - 3\right) + \frac{1}{D}(J-1)^2 \tag{2}$$

As shown in formula (2), λi is the three principal elongation ratios, μp and αp are material parameters that control the nonlinear response of different orders, J=det(F) is the volume ratio, F is the deformation gradient, and D is the incompressibility penalty factor [23,24]. The parameter D serves as a penalty factor enforcing near-incompressibility within the constitutive formulation. Although natural leather exhibits porous microstructure and potential compressibility under high stress, the assumption of quasi-incompressibility remains valid for the typical strain range and impact conditions encountered in drumhead vibration. Leather fibers are densely packed and laterally constrained during membrane vibration, leading to negligible volume change in the plane stress state considered. The penalty factor D is assigned a sufficiently small value to allow minimal volumetric variation while ensuring numerical stability and consistency with the transverse isotropy assumption. This treatment aligns with prior hyperelastic modeling of fibrous biological membranes where volume changes are secondary to shear-dominated deformations.

Since the drum surface thickness is much smaller than the wavelength, assuming a plane stress state and ignoring transverse shear, the governing equation for the damped nonlinear motion is derived as follows:

$$\rho h\ddot{u} + c\dot{u} - \nabla \cdot P = f_{\text{impact}} \quad (3)$$

As shown in formula (3), ρ is density, h is thickness, $P=\partial W/\partial F$ is the first Piola-Kirchhoff stress tensor. The term $c\dot{u}$ represents linear viscous damping, where c is the equivalent viscous damping coefficient per unit area introduced to model the dissipative behavior observed in leather under transient excitation. The impact force f_{impact} is applied by an electromagnetic impactor and modeled as a spatiotemporal Gaussian pulse. This equation constitutes the core partial differential constraint of the subsequent physical information neural network [25,26]. The damping coefficient c is treated as an additional material parameter within the trainable parameter vector θ.

To determine the initial values of the Ogden model parameters, uniaxial tensile and dynamic mechanical analysis were performed on three typical types of natural leather (cow back leather, goatskin, and Burmese python belly leather). The sample thickness was uniformly controlled to be about 0.8 mm, and the test environment temperature and humidity were 23°C and 50% RH. The obtained material parameters are listed in Table 1.

TABLE 1. Ogden Constitutive Parameters of Three Types of Natural Leather

Leather type	Density (kg/m³)	Thickness (mm)	Young's modulus in principal directions (MPa)
Bovine Backhide	980	0.80 ± 0.03	86.5 (radial) / 72.1 (circumferential)
Goatskin	950	0.81 ± 0.04	74.3 (radial) / 65.8 (circumferential)
Python belly skin	1020	0.79 ± 0.03	98.7 (radial) / 81.4 (circumferential)

The parameters in Table 1 serve as the initial physical prior values for training, ensuring that the network converges within a reasonable material space. This modeling framework fully preserves the large deformation nonlinearity, fiber orientation anisotropy, and initial tension effect of leather materials, providing a rigorous dynamic basis for subsequent data-physics fusion.

B. PHYSICAL INFORMATION NEURAL NETWORK ARCHITECTURE DESIGN

To achieve a differentiable mapping between the material parameters of the leather drumhead and the timbre, this paper constructs a physical information neural network. The core of this network is to embed the nonlinear shell dynamics equation and the hyperelastic constitutive relation as hard physical constraints into the network training process. The network adopts a fully connected architecture. The input layer contains excitation parameters (radial coordinates of the striking position rimp and force F0) and a trainable material parameter vector $\theta=[\mu1,\alpha1,\mu2,\alpha2,D]^\top$. The output layer synchronously generates the drumhead displacement field u(r,θ,t) and acoustic feature vector s. The network automatically differentiates and calculates the higher-order derivative of the displacement field with respect to the spatiotemporal coordinates, and substitutes it into the control equation to construct the physical residual term. This residual, together with the measured displacement data and the acoustic spectrum features, constitutes a composite loss function [27,28]. The material parameter vector θ is not used as a fixed input, but is initialized by an independent embedding layer and updated with backpropagation, forming an end-to-end differentiable path from the timbre target to the material constitutive [29,30]. The network training adopts a multi-task weighted strategy. The physical loss, displacement data loss and acoustic spectrum loss are dynamically balanced according to preset weights to avoid the physical constraints being overwhelmed by the data terms. This solution approximates the measured Multimodal Response through joint optimization to solve the partial differential equations, so the parameters can be identified without being bound by material labels, thanks to its total architecture. Figure 1 shows the structure of this solution, which includes the material parameter embedding Layer, Physical Constraint Module, Vibration-Acoustic Coupling Interface, Dual Channel Output Mechanism.

The components of the model work together as shown in Figure 1. The material parameter embedding layer takes in a set of material parameters and will then update them during the training process. The physics constraint module takes in information from the nonlinear dynamic equations and constitutive models during the training process to create a training loss term that enforces the physical constraints of the model. The spatiotemporally coupled vibration-acoustic interface matches the drumhead displacement to the acoustically generated features to allow the output of the model to satisfy all physical constraints and target timbre characteristics. Finally, a dual-channel output provides an independent output of the drumhead displacement and the timbre feature vectors.

C. ACOUSTIC REPRESENTATION OF TIMBRE CHARACTERISTICS AND CONSTRUCTION OF OPTIMIZATION OBJECTIVES

Timbre, as the core perceptual dimension of the acoustic performance of percussion instruments, needs to be objectively represented by taking into account spectral structure, transient onset characteristics, and energy decay behavior. Traditional low-dimensional indicators such as fundamental frequency or decay time cannot reflect the rich harmonic structure and modal coupling effect generated by the nonlinear vibration of the leather drumhead [31,32]. This paper uses the higher-order statistical moments of the Mel spectrum as the mathematical representation of timbre. This representation maps the audio signal to the Mel scale through short-time Fourier transform, and

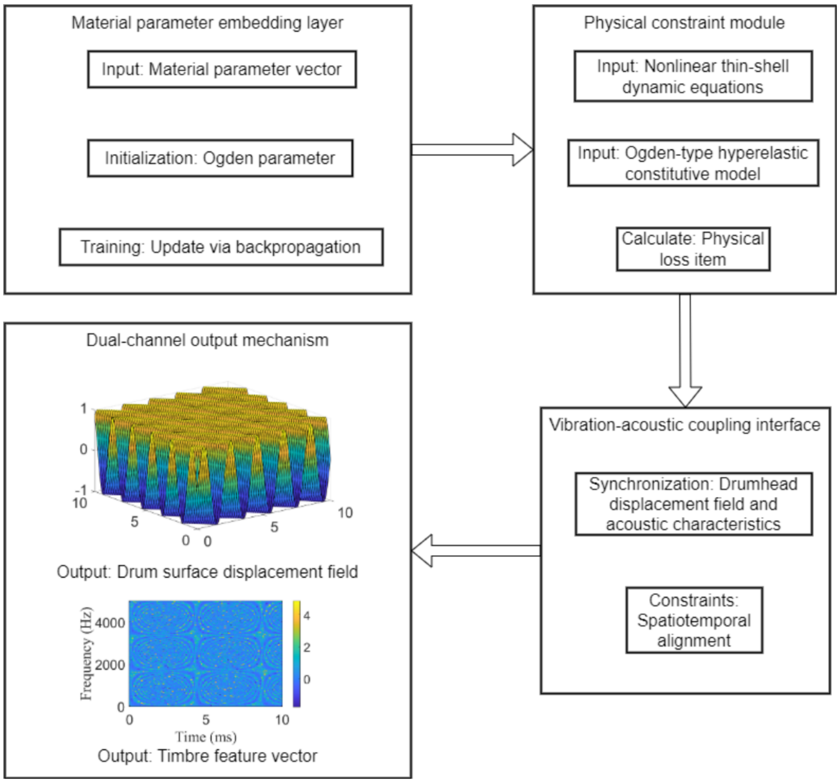

FIGURE 1. Neural Network Architecture for Physical Information

then calculates the mean, variance, skewness, and kurtosis of the probability distribution of the spectral amplitude for each frame to form a four-dimensional feature vector. This vector is sensitive to the energy distribution of high-frequency modes, the asymmetry of the spectral envelope, and the degree of harmonic concentration, and is strongly correlated with perceived brightness, fullness, and crispness in subjective listening. This feature vector serves as the acoustic output target of the physical information neural network architecture and, together with the displacement field data, constrains the network training [33,34]. In order to establish the physical relationship between sound and vibration mapping, the transient displacement field of the drumhead surface and the far-field sound pressure signal are collected simultaneously to ensure that the two are strictly aligned in time and space. The displacement field was reconstructed by a high-speed optical system with a resolution of 0.1 mm and a time step of 0.2 ms; the acoustic signal was acquired by an 8-channel ring microphone array and then beamformed to extract the sound pressure in the main radiation direction [35]. The two together constitute a multi-physics field supervision signal, which forces the network to simultaneously satisfy the structural dynamics and acoustic radiation laws during the learning process. The coupling characterization relationship is shown in Figure 2.

Figure 2(a) shows the spatial variation of the displacement field over time, revealing the influence of highfrequency oscillations and nonlinear effects. In the displacement field evolution diagram, the displacement change exhibits a gradually increasing oscillation pattern over time, with the oscillation amplitude increasing under the influence of the nonlinear term. Figure 2(b) shows the relationship between frequency and time, where the changes in the high-frequency component reveal the manifestation of nonlinear effects in the material.

D. INVERSION MECHANISM OF DIFFERENTIABLE MATERIAL PARAMETERS

Traditional inverse problem solving relies on iterative optimization or parameter scanning, which is computationally expensive and prone to getting trapped in local minima, making convergence difficult in the absence of good initial values. This paper constructs the material parameter vector θ as a trainable embedding layer in a neural network to achieve end-to-end differentiable inversion from target timbre features to constitutive parameters. The initial value of this embedding layer is set by the Ogden parameter and is updated synchronously with the gradient of the loss function during training, without the need for an external optimizer. The inversion target is defined by the user-specified timbre feature vector, represented by the four-dimensional higher-order moments of the Mel spectrum. The network automatically adjusts θ through backpropagation, ensuring that the generated displacement field and acoustic features simultaneously approximate the physical equations and the target timbre. To ensure inversion stability, the loss function incorporates physical rationality constraints on the constitutive parameters, including $\mu_p > 0$, $|\alpha_p| < 3$, and

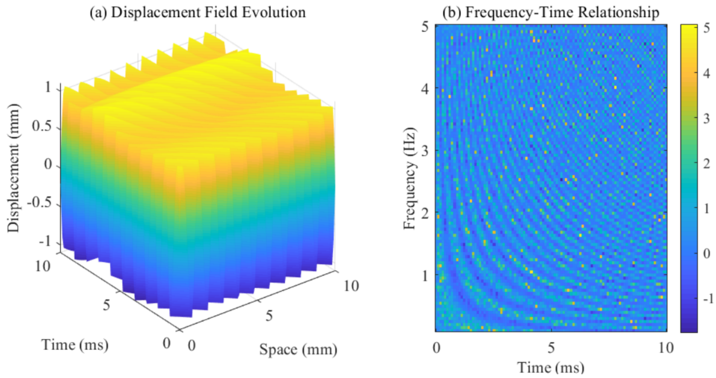

FIGURE 2. Coupling Relationship between Drumhead Displacement Field and Audio Signal Spectrum: (a) Drum Surface Displacement Field; (b) Audio Signal Spectrum

$D < 10^{-3}$, suppressing non-physical interpretations through soft penalty terms. The two-step method used in training consists first of holding θ fixed, while only optimizing the weight of the network to match the measured values. The second step will unfreeze θ and optimize the network and material parameters together in order to gain higher quality results for all inversions. By doing this, it closes the gap between the simulation of the model with physics and the optimization loop created by the conventional method used to correlate physical properties with data collected through experiment. As a result, material choice is presented as a differentiable learning task. The arrangement of hyperparameters in training determines how well constraints imposed by physics can be satisfied versus fitting the data; the selected hyperparameters are shown in Table 2.

TABLE 2. Training Hyperparameters and Loss Weight Configuration

Hyperparameter	Value	Description
Initial learning rate	1×10^{-3}	Adam optimizer with cosine annealing
Physics loss weight	0.6	Controls the impact of the dynamic equation residual
Displacement field loss weight	0.25	Aligns with high-speed optical measurements
Spectral feature loss weight	0.15	Matches Mel-frequency higher-order moments
Material parameter L2 regularization coefficient	1×10^{-4}	Suppresses overfitting
Constitutive parameter penalty weight	0.05	Constrains the physical range of parameters
First-stage training epochs	8000	Freezes material parameters during training
Second-stage training epochs	12000	Joint optimization stage

Table 2 includes the learning rate, weights of each loss term, regularization coefficients, and number of training epochs. All configurations are determined on the validation set through grid search to ensure model convergence and generalization ability.

III. EXPERIMENTAL DESIGN AND DATA ACQUISITION

A. DRUM SURFACE SAMPLE PREPARATION AND MATERIAL CHARACTERIZATION

In this study, three types of natural leather commonly used in ethnic and symphonic percussion instruments were chosen for experimentation: cowhide, goatskin, and Burmese python belly skin. All leather samples underwent the same batch processing and were tanned using the same vegetable tanning process to ensure that the composition of the tanning agents and degree of cross-linking were consistent between samples. The drum heads were then attached to rigid aluminum drum shells that were 298 mm in diameter and 200 mm deep. Pre-tensioning was applied along the edges using a 12-point mechanical clamp system, and the tension values of the drumheads were immediately gauged after installation with a digital tension meter. Four levels were set: 200 N/m, 350 N/m, 500 N/m, and 650 N/m, covering the typical performance tension range. Uniaxial tensile testing of materials was performed using the Instron 5969 testing machine in both radial and circumferential directions at a tensile rate of 5 mm/min, with a gauge length of 50 mm, with each material being tested six times to evaluate the variability of the results. A dynamic mechanical analysis was performed on each of the materials at a frequency between 1 Hz and 100 Hz using a 0.1% static strain to measure the storage modulus and loss factor of each material. The individual test data was then used to determine the Ogden parameters for each of the materials and to provide the input parameters for the modeling that will take place next.

B. CONSTRUCTION OF EXCITATION-RESPONSE SYNCHRONOUS MEASUREMENT SYSTEM

A multimodal synchronization data acquisition platform was developed for the concurrent collection of vibration and acoustic emission data from the drumhead structure. The excitation unit consisted of an electromagnetic impactor that used a hard nylon hammer, 12 mm in diameter, to deliver mechanical impacts. The amplitude of the impact force could be finely adjusted with a programmable power supply that had a range of 0.5–5 N (0.1 N accuracy) for approximately 0.8 ms during each impact. The three typical locations of impact used throughout the radius of the drumhead were 0.3 R, 0.6 R, and 0.9 R, where R is defined as the radius of the drumhead. The structural response was captured using a high-speed camera (Phantom v2512) operating with a frame rate of 5000, exposure time of 50 μs and spatial resolution of 0.05 mm/pixel using digital image correlation technology. All devices were synchronized to the same high-precision clock with a time jitter of less than 10 μs, allowing for precise alignment of the displacement field with the sound pressure signal along the time axis. The sound propagation delay between the drumhead surface and the microphone array was explicitly corrected to achieve strict spatiotemporal alignment. The time-of-flight for the acoustic wave was calculated based on the measured distance from the drumhead center to each microphone and the nominal speed of sound under laboratory conditions. The recorded acoustic signals were then shifted backward in time by this delay prior to feature extraction. The data acquisition software, developed in Python, automates the collection of excitation parameters, secures multi-channel audio files, and allows for continuous writing of high-speed image streams to create a combined structure-acoustic dataset. Calibration of the entire system uses cross-validation of the results obtained from a standard sound source, using a laser vibrometer, with overall displacement amplitude errors of less than 3.0% and sound pressure level deviations of less than $\pm$ 0.8 dB.

IV. RESULTS ANALYSIS

A. MATERIAL PARAMETER INVERSION ACCURACY EVALUATION

The accuracy of the parameter inversion used to determine Young's modulus, shear modulus, and the damping coefficient for three leather types (cow back leather, goatskin, Burmese python belly skin) was investigated using a nonlinear physics-informed neural network-based method. The performance of the parameter inversion method was also evaluated in relation to its convergence with errors measured during training. The parameter inversion method is corroborated by comparing the actual and determined material properties, so determining the success of the method without use of material labels. Figure 3 illustrates the correlation between parameter inversion error for each material type and the change in error associated with the iterations of training.

Figure 3(a) shows that Bovine Backhide has the lowest inversion errors among the three hides measured (Young's modulus 2.3%, Shear Modulus 2.5% and 2% Damping Coefficient) compared to Goatskin's Inversion errors (3.1%, 3.3% and 3% Damping Coefficient) and Burmese Python's (4.7%, 4.9% and 4.5%). As seen in Figure 3(b) there is also rapid convergence of errors with increased iterations. Error values for Young's Modulus, Shear Modulus, and Damping Coefficient all decreased significantly within the first 30 iterations of testing as demonstrated. This is due to an increase in accuracy caused by using physical constraints combined with data computational methods. The results of testing demonstrate that the method used will produce controlled inversion errors within a low range indicating high accuracy of parameter predictions.

B. CONSISTENCY ANALYSIS OF TIMBRE FEATURE RECONSTRUCTION

The timbral features of a leather drumhead were reconstructed using a physical information neural network model. The ability of the model to accurately reproduce timbral characteristics was evaluated by comparing the timbres produced by model inversion against the spectrum of the actual acquired audio signals. Data were collected from leather drumheads under a variety of striking conditions. Audio signals collected were pre-processed and converted to spectral features for analysis. The results of this process will allow evaluation of the effectiveness of the model used for timbral reconstruction as well as give guidance for future timbre optimization/control. A graphical representation of the similarity and differences of the spectra between actual timber sample acquired through measurement and reconstructed spectrum acquired through data processing can be seen in Figure 4.

As can be seen in Figure 4, the curves representing the actual spectrum and the reconstructed spectrum are very similar in the lower frequency ranges (0–1000Hz). However, there is a large discrepancy between the actual and reconstructed spectra at the higher frequencies. The discrepancy may be attributed either to the fact that the model does not have a sufficient amount of training data at higher frequencies or to the fact that the model itself does not have a good enough frequency response to reconstruct the high frequency portion of the spectrum. Another possible explanation for the model not accurately reconstructing the highfrequency data is that a nonlinear response was present when processing the input signal at high frequencies or the signal was very noisy.

C. STABILITY ANALYSIS OF MATERIAL-TIMBRE MAPPING RELATIONSHIP UNDER TENSION CONTROL

The purpose of this experiment was to assess the tonal characteristics of various leather materials, including cow hide, goat skin and Burmese Python, at different levels of tension on those materials, as well as the interaction between selection of leather materials and tension on that leather material and the effect of tension on the ability to reproduce and stabilize at tonal feature level through tension adjustment of the various leather types. A graphic presentation is provided in Figure 5 to illustrate how different types of leather material contribute to the composition of tonal features at various levels of tension.

The reduction of the three materials' contribution to timbre as pretension increases illustrates this clearly in Figure 5(a). The percentage of contribution is as follows: cowhide dropped from 68% to 38%; sheepskin from 62% to 34%; and python skin from 59% to 31%. These reductions in

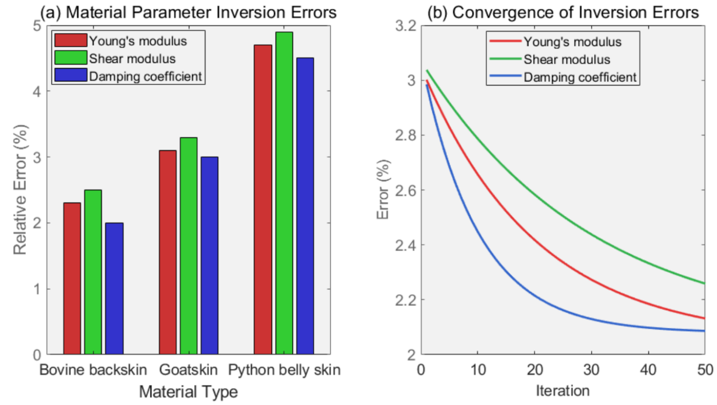

FIGURE 3. Material Parameter Inversion Error and Convergence Curve: (a) Material Parameter Inversion Error; (b) Error Convergence

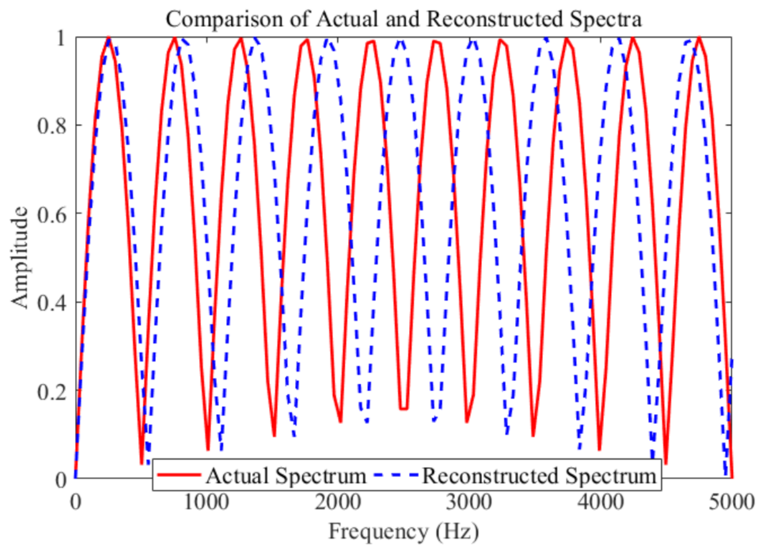

FIGURE 4. Comparison of Reconstructed Timbre Features and Actual Spectrum

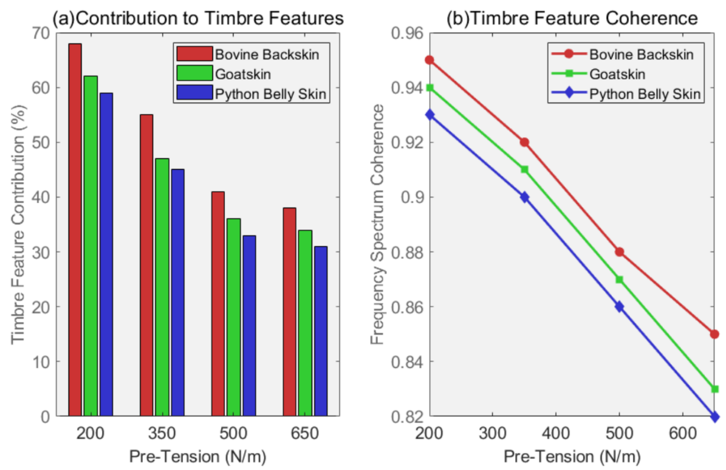

FIGURE 5. Influence of Material and Pretension on Timbre Characteristics: (a) Contribution to Timbre Characteristics; (b) Consistency of Timbre Characteristics

the materials' influence may result from increased stiffness in the materials with increased pretension. As pretension is applied, the deformation of the leather fibers continues to increase which can result in less contribution from the leathers to the timbre. There was also a similar decrease shown in the spectral coherence data as illustrated in Figure

5(b). The spectral coherence for cowhide decreased from 0.95 to 0.85, for sheepskin from 0.94 to 0.83, and python skin from 0.93 to 0.82. Increased pretension may also change the elasticity characteristics of the materials and the energy transfer characteristics of the materials, which would affect the stability and clarity of the timbre produced. In summary, the data represent how the various materials contribute to timbre characteristics under various pretension conditions and how the physical properties of the materials are the critical component of the timbre created.

D. ABILITY OF NONLINEAR CONSTITUTIVE MECHANISMS TO CAPTURE HIGHER-ORDER MODAL RESPONSES

This experiment compared nonlinear and linear constitutive models used to analyze the differences in leather drumhead vibration response at various frequencies and modes. Nonlinear constitutive models had advantages over linear constitutive models at higher frequency, when compared with simulated vibration responses at various frequencies and modes. Nonlinear constitutive models were evaluated to show the differences in capturing high-frequency response accuracy differences between nonlinear and linear constitutive models. The errors between the nonlinear and linear constitutive models are shown below in Figure 6 for the differences in responses relative to the various frequencies and modes used.

As shown in Figure 6, the error difference between linear and nonlinear constitutive models is small in the low-frequency region, while in the high-frequency region, the error of the nonlinear constitutive model is lower than that of the linear model. This phenomenon is closely related to the modal vibration characteristics in the high-frequency region. The nonlinear constitutive model can better capture the nonlinear behavior of the material, especially in the high-frequency modes, where the nonlinear response of the material has a more significant impact on the vibration characteristics. The linear model fails to fully consider these nonlinear effects in these high-frequency modes, resulting in a larger error than the nonlinear model. The results indicate that nonlinear modeling has higher accuracy in high-frequency response prediction.

E. THE INFLUENCE OF AMBIENT HUMIDITY ON THE STABILITY OF MATERIAL-TONE MAPPING

When studying the acoustic properties of natural leather, the influence of environmental humidity on material properties cannot be ignored. The hygroscopic-desorption characteristics of natural leather cause changes in the moisture content of its fiber network under varying humidity conditions, thus affecting its mechanical properties, especially Young's modulus and damping coefficient. These changes can significantly impact the timbre of the leather. Therefore, this experiment conducted excitation-response experiments on cowhide drumheads under different humidity conditions (30%, 35%, 40%, 45%, 50%, 55%, 60%, 65%, 70%), recording the changes in mechanical parameters under different humidity levels. The data were then inverted and reconstructed using a corresponding model to evaluate the influence of humidity on the timbre of the leather. The experimental results are shown in Figure 7.

Figure 7(a) shows that the Young's modulus decreases with increasing humidity, starting at 100 GPa and decreasing to 81.4 GPa at 70% humidity, a decrease of 18.6%. Figure 7(b) shows that the damping coefficient increases with increasing humidity, from 0.5 to 0.62. The reduction of Young's modulus is related to the presence of water in the leather fiber structure as a result of higher atmospheric humidity, which reduces the stiffness of the fibers and affects the mechanical properties of leather. The increase in the damping coefficient may have been caused by improvements in the internal damping characteristics of the leather due to an increase of water in the leather, which increases its energy absorbing ability. Humidity has a major effect on the properties of leather, which suggests that physical properties of leather and other materials are affected significantly by environmental changes and that these changes may affect the tone stability.

The observed increase in the damping coefficient with humidity arises from a coupled physicochemical mechanism. Water absorption by leather fibers contributes not only to a change in internal damping but also introduces an added mass effect and a reduction in fiber stiffness. The increase in material density due to moisture uptake can shift the system's natural frequencies. However, the measured increase in damping is a net result dominated by the enhanced viscoelastic dissipation within the softened fiber matrix. The constitutive model inversion captures this combined effect as an effective increase in the damping coefficient, reflecting the integrated influence of moisture on the dynamic mechanical response rather than an isolated change in a single property.

V. DISCUSSION

A. SCIENTIFIC EXPLANATION OF TRADITIONAL MUSICAL INSTRUMENT MAKING EXPERIENCE

This study provides preliminary scientific verification and quantitative interpretation of some traditional drum-making experiences through interpretable physical embedding models. For example, craftsmen often select materials based on the toughness and elasticity of leather; the corresponding constitutive parameters in this paper can be quantitatively expressed through inversion. Traditionally, pitch and timbre are changed by gradually increasing tension using tuning ropes. The results of this study show that increasing pretension suppresses the contribution of material nonlinearity to timbre, which is consistent with the perception that higher tension leads to a brighter and more stable timbre. Furthermore, the differences in material parameters derived by the model (such as the high Young's modulus of Burmese python belly skin) have a physical basis correlated with the auditory characteristics of different leathers, such as

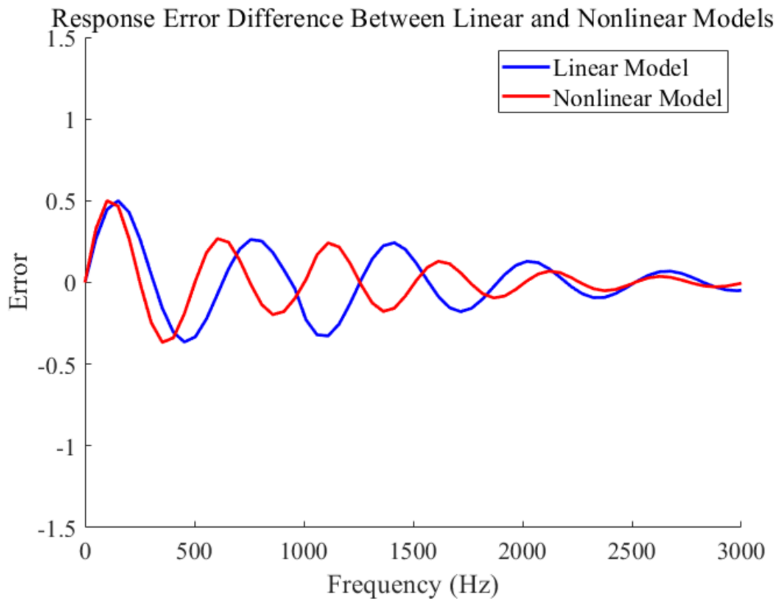

FIGURE 6. Analysis of the Difference between Linear and Nonlinear Constitutive Responses

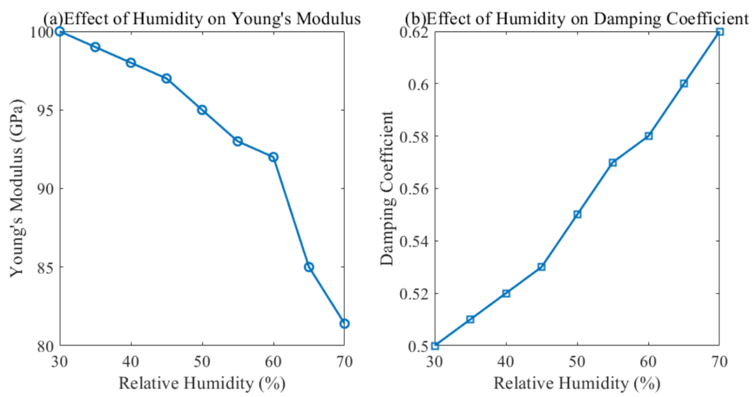

FIGURE 7. Effect of Humidity on Young's Modulus and Damping Coefficient: (a) Relationship between Young's Modulus and Humidity; (b) Relationship between Damping Coefficient and Humidity

crisp and full sounds, in actual use. This suggests that the material-sound effect correlation mechanism inherent in traditional experience may be transformed into a computable and inheritable knowledge system through modern modeling methods.

B. APPLICATION PROSPECTS FOR DIGITAL RESTORATION

In musical instrument manufacturing and new material research and development, the model can be used to guide the development of new synthetic or composite drumheads. By setting ideal acoustic performance targets, the required material mechanical properties can be solved in reverse, thereby guiding material formulation and structural design. Combined with additive manufacturing technology, customized drumhead manufacturing oriented toward acoustic performance can be realized in the future. In addition, an intelligent musical instrument design platform integrating material databases, physical models, and auditory feedback can be developed, enabling makers to virtually listen to timbre effects under different combinations of materials, tension, and geometric parameters. This approach could accelerate product development cycles and promote the transformation of musical instrument manufacturing towards a data-driven, performancepredictable modern model.

VI. CONCLUSION

This paper focuses on the material selection and timbre control mechanism of leather drumheads for percussion instruments. It proposes a physical information neural network based on nonlinear hyperelastic constitutive embedding. By embedding Ogden-type constitutive relations and thin-shell nonlinear dynamic equations as physical priors into a differentiable framework, and jointly optimizing the displacement field measured by high-speed optical measurements and the timbre characteristics characterized by higher-order moments of the Mel spectrum, an end-to-end inversion from the target timbre to the leather material parameters is achieved.

Experimental verification shows that the relative errors of this method in inverting Young's modulus, shear modulus, and damping coefficient of cowhide are 2.3%, 2.5%, and 2%, respectively. By providing a scientific framework that is computable, predictable and interpretable, this research has established an alternative to traditional techniques, which rely on the use of empirical prototyping and linear assumptions. This framework will have direct applications in accurately restoring ethnic percussion instruments, designing acoustic performance directions, and constructing digital sound libraries. It will provide the theoretical and methodological framework for using data-driven paradigms in the evolution of traditional methods of instrument manufacture.

AUTHOR CONTRIBUTIONS

Writing-original draft preparation –Wangcheng Shi; writing-review and editing –Sihui Huang. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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