Material Identification System with Sound Simulation Assisted Method in VR/AR Scenarios

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ABSTRACT

We propose a new model using transfer learning method in motivation of specifying and identifying material of an object by knocking in VR/AR applications. Different from the traditional contact knocking material/object identification method, we apply the sound simulation method to enlarge the training dataset containing various models and materials in real-world scenarios. Our approach is based on Domain-Adversarial Training of Neural Networks that learns from the pre-collected simulated and corresponding real knocking sound to extract their common features determined by different materials. Given the scanned 3D model and the real knocking sound from users, we present an incremental learning model using the features extracted by pre-trained transfer learning model to generate the final material classifier. We perform an overall evaluation showing that our system achieves around 93.3% accuracy of identifying materials, which is much higher than the accuracy mentioned in previous work.

CCS CONCEPTS

• **Human-centered computing → Interaction design**.

KEYWORDS

Material Identification; Modal Sound; Transfer Learning

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1 INTRODUCTION

In recent years, the development of Augmented Reality (AR) and Virtual Reality (VR) technology offers a host of applications in fields including education, training, entertainment, medical treatment, etc., which deepens the yearning of people for their growing demands and expectations in virtual world. Key point now is to determine and strengthen the relationship and connection between reality and virtual world, thus realizing the personalized customization for different users and bringing the sense of belonging. If possible, users would prefer to scan objects around in real world and import 3D models to VR/AR scene for fun and familiarity [17]. Problem occurs that without the material and inner structure information of the 3D model, interactions are strictly limited to simple ones including drag, rotate, copy, etc. even without any sound effects. This inversely arouses users' strangeness and their antipathy to these "soulless" scanned 3D models.

To detect or specify the material and structure of the newly scanned 3D models, existing methods can be classified into, according to their principles, motivations and target materials, the contact knocking approach [5, 7, 15, 19], vision-based approach [3, 10, 16], and resonance spectroscopy approach [6, 11].

Contact knocking is to gently tap the test object and generate the sound. Since the elasticity of the object and its internal friction [12, 13] , which are determined by its material and structure, influence the frequency of the sound, we can identify the material composition and structure of the 3D models by analyzing the knocking sound. However, for better training results, large amounts of contact knocking sound data is required, which means it is hard and impossible to simply implement the current knocking method considering various object models and numerous kinds of materials.

Vision-based method is to analyze the image of the test object using deep learning techniques. However, the structure of the scanned 3D models remains unknown and the decorations or paintings on object surface may interfere with the classification result. Acoustic resonance spectroscopy is used to identify materials, especially liquids, and their compositions. It utilizes the acoustic property of liquids and try to find the natural frequency of the test material, which helps to identify the liquids since natural frequency is dependent on composition of liquids [2]. For our goal, however, this can not be used on solid object to identify its material.

To apply the contact knocking method while avoiding annoying and exhausting knocks by users to get training data, we utilize the sound simulation method to generate enough simulated knocking sound data for better learning and training for our models. For users, he/she needs to scan the target object using the camera on phone to generate its 3D model, then follow the instructions to knock at some certain positions (commonly the center of the flat surface for better performance) of the target object and collect the knocking sound using microphone. Challenges come with the inevitable difference between simulated knocking sound and the real knocking sound of the same object. Due to various environmental noise and different knocking strength and angle, the real sound cannot be exactly reproduced by simulation. Next, though we instruct our user to knock some certain points of the object, errors may occur when the user operates, causing unexpected randomness of the exact knocking position. Also, since the scanned 3D models from users can be made of new materials that have not been trained and learned even within our vast simulated sound dataset, the overall classification performance may not be within expectations on new materials.

Considering above challenges, to deal with the difference between the simulating and real knocking sound data, we use Domain-Adversarial Training of Neural Networks (DANN) [4] method. The simulated and real knocking sound data as the source and target domain, respectively. At training stage, for each knocking position, we use the simulated sound and 4 independent real knocking sound for learning and training, and 1 more independently collected real knocking sound data for testing to extract the domain-independent features of the sound data. And, to address the unexpected knocking position randomness, we now train with simulated and real sound data of 80% of the selected knocking positions and test with the remaining 20% on the same surface to offset the effect of the random knocking position. Finally, considering the effect of new materials, we change the test set to the sound of object with materials not in the training set. By learning and training then, we can assure the accuracy of our model when classifying sound data knocking at objects with new materials.

Our key contributions are summarized as follows:

-We design a system to detect and identify the material and structure of 3D model using contact knocking method.

-We adopt sound simulation to expand the size of knocking sound dataset and avoid numerous times of repeated knocking.

- We use DANN for transfer learning on simulated and real knocking sound data and alter the training and testing set for the accuracy and robustness of our model.

2 METHOD

2.1 Simulating Sound

Current researches have found that given mass matrix and stiffness matrix of the target object as input, we are able to calculate the final acoustic signal output in the case of activating an impulse on certain knocking position. Applying modal analysis [8] onto the input mass and stiffness matrix using finite element analysis, we can generate the vibration modes and get the modal parameters. Then given an impulse signal (user's knock), using the Helmholtz equation, we can generate the acoustic signal of the knocking sound.

Therefore, factors including shape, material, structure, etc. of the target object which affect input mass and stiffness matrix of the object ultimately determine the knocking sound. Now, the problem can be defined as: given 1) a 3D model of the target object, 2) the knocking position, and 3) the real knocking sound generated by user, we want to detect and identify the material of the part the user knocked at. Since knocking sounds are affected by various factors mentioned above, and their influence ratio cannot be simply quantified, we cannot simply classify materials by comparing and matching the recorded sounds with that of different materials to identify the material. Therefore, we first simulate the knocking sounds using to the scanned 3D model and use it to train a classification model.

Previous research shows that the knocking sound of an object is the composition of different vibration modes of the object. Modal analysis is the method used to calculate its modal. When we knock at an object, we can use the modal data to calculate the vibration modes of the object. After that, we can compute the acoustic transfer function to generate the final sound. To acquire real-time performance of knocking sound synthesis, we can pre-compute the modal and transfer function to get vibration modes and transfer maps. When we input the knocking position, we simply use the pre-computed vibration modes and transfer maps to generate the final sound.

2.1.1 Modal Generation. We use traditional linear modal analysis technique to calculate the modal of an object. As the study of modal analysis shows, for a multi-degree of freedom damping system, the vibration differential function is:

$$M\ddot{x} + C\dot{x} + Kx = f(t) \tag{1}$$

Where M is the mass matrix of the system, K is the stiffness matrix of the system, x is the displacement matrix, $\dot{x}$ is the speed matrix, $\ddot{x}$ is the accelerator matrix. To get the mass matrix and stiffness matrix, we use isosurface stuffing to convert the surface mesh of an object to tetrahedral mesh. Then we use the mass and stiffness matrix of the tetrahedral mesh to calculate the differential function.

Since the real damping matrix is very complex, to simplify the problem, we use Rayleigh damping to get an approximate result. Rayleigh damping is the composition of mass matrix and stiffness matrix:

$$C = \alpha M + \beta K \tag{2}$$

By solving the first differential function, we can get the vibration mode of the system is:

$$x = \sum_{i=1}^{n} \varphi_i Y_i sin(\omega_{di} t + \theta_i) \tag{3}$$

where φ is the eigenvector of the differential function. It shows that the object only has n independent vibration mode. We can use these vibration modes to represent the vibration of the object.

2.1.2 Acoustic Transfer. After getting the vibration modes of an object, we need to calculate the sound propagating function to get the air pressure profile at the microphone position. We first use Nemann boundary condition to transfer the surface vibration acceleration into air. The definition of the Nemann boundary condition is:

$$\frac{\partial p}{\partial n} = -\rho a_n(x, t), \ x \in \Gamma \tag{4}$$

where $a_n(x,t)$ is the surface acceleration. Then we use 3D wave function to solve the wave propagation problem. The acoustic pressure, $p(x,t)$, satisfies:

$$\nabla^2 p - \frac{1}{c^2}\frac{\partial^2 p}{\partial t^2} = 0 \tag{5}$$

where c denotes the speed of sound in air.

Consider harmonic pressure solutions of the form:

$$p(x,t) = p(x)e^{+i\omega t} \tag{6}$$

By substituting the above function into the wave function, we can get Helmholtz equation:

$$\nabla^2 p(x) - k^2 p(x) = 0 \tag{7}$$

where $k = \frac{\omega}{c} = \frac{2\pi}{\lambda}$. To calculate this function, tradition way is using fast multi-pole method. [26] But the computational cost of this method is very high. So we use finite difference time domain method mentioned in [23]. It uses GPU to accelerate computation which can reduce the computational time significantly.

2.1.3 Click Sound Synthesis. After the above two steps, we get pre-computed vibration modes and acoustic transfer maps. Then we can use the knocking position data and knocking strength data to calculate the surface vibration states using pre-computed vibration modes. Then we use the pre-computed sound transfer map of each vibration mode to calculate the air pressure profile at the microphone position separately and linearly combine all the air pressure profile to synthesis the sound.

2.2 Classification: Identify Material

In this part, we have known the knocking position (roughly) and the real knocking sound collected by users. As a simple and direct view, traditional approach to identify materials using contact knocking method used to collect the real knocking sound signal for enough times repeatedly to establish the training dataset. Then, apply the deep learning model to train these sound signals generated by knocking at surface of various materials, the output classifier is able to identify the material of the user's target object with one specific knocking sound signal. No need of the 3D model, the overall performance is limited by the changing structure and material of the object, since it may differ greatly from the collected training data inside the training set.

We, therefore, provide a new learning method utilizing the sound simulation and the scanned 3D model. First, we use DANN for transfer learning on the simulated and real knocking sound data of various object collected in advance as the source and target domain. The training set is now set to be the simulated and real knocking sound, and we change testing set to gradually test and improve the overall classification performance. Finally, using the 3D model, we simulate knocking sound with various pre-trained materials as input, and do the incremental training with these simulated sound signals. The final classifier is expected to achieve better performance than traditional method to specify and identify the material of the target object.

3 SYSTEM

Our system flow is shown in Fig. 1. In short, our system will first ask the user to use a camera on his/her mobile phone to scan the object

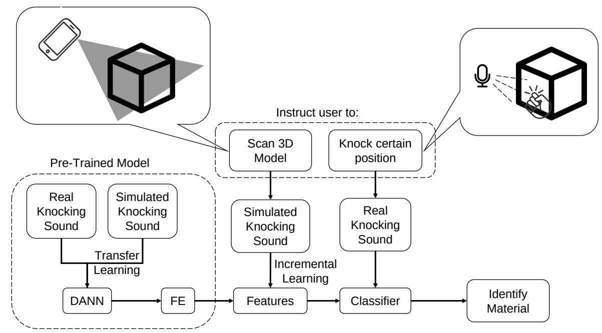

Figure 1: System flow

and construct a 3D model, and then instruct which part and what knocking position is required to knock at and generate the knocking sound. Combined with our pre-trained model, the latest classifier will specify and identify the material of the object according to the knocking sound.

4 EVALUATION

4.1 Experiment Setup

In the experiment, we select 8 different models to collect sound data and do sound simulation. For several models, we collect data from multiple surfaces. The detailed information of collected data is in table 1. In the experiment, a single user used the tip of a tool made of iron to knock at the objects. For each point we knocked 5 times and we knocked at 437 points in total. Since we can set the stiffness matrix in modal function to represent non-uniform materials and most of the surface are made of a single uniform material, to simplify the problem, all the materials we collected are uniform.

4.2 Microbenchmark

4.2.1 Same Knocking Position. First, we evaluate the performance of the model on the scenario when a user knocks at one of the positions in our training set. We use 4 real knocking sound of each knocking position and its corresponding simulation sound as training set to train our model, and the last real knocking sound as testing set to show the performance of our model. The testing accuracy is about 98%.

4.2.2 Different Knocking Position. We then evaluate the performance of the model on the scenario when a user knocks at a new position on one of the surface in the training set. We use sound of 80% knocking positions of each surface as training set. The knocking sound data of 20% remaining positions are used as testing set. The testing accuracy is about 95%

4.2.3 Different Model. Lastly, we evaluate the performance when a user knocks at a brand new model. We use 12 surfaces of total 13 surfaces as training dataset each time. The remaining 1 surface is used as testing dataset. The average testing accuracy is about 92%.

Table 1: Dataset Description

Knocked objects	Number of knocking surfaces	Material of each surface	Number of knocking points of each surface
Short wood plate	1	wood	45
Long wood plate	1	wood	60
Wooden table	3	wood, wood, wood	36, 30, 32
Wooden partition	1	wood	21
Iron plate	1	iron	25
Aluminum plate	1	aluminum	25
Acrylic board	1	acrylic	35
Speaker	4	wood, wood, PVC, PVC	25, 45, 30, 28

4.3 Method Evaluation

4.3.1 overall performance. In our application, we need to identify the material of the object that users knock at. We use VR to scan the object and get its 3D model. The traditional way is to only use the data from the training set to train a model to classify the materials. In our method, we first use the data from training set to train a transfer model. Then we use all the materials to generate different simulation sound using the 3D model from the testing set. We use the different simulation sound to train a classifier. Then we use this new classifier to classify the real knocking sound to determine which material the object is. The result shows that when using the traditional method the testing accuracy is about 75.6%. When using our method, the testing accuracy is about 93.3%.

5 RELATED WORK

The following section provides an overview of the current state of sound simulation method, as well as commonly used material identification approaches including acoustic-based ones and others.

To simulate the knocking sound, the whole process can be divided into 3 parts: modal generation, acoustic transfer, and click sound synthesis. Wang et al. [22] presented KleinPAT, a new time-domain algorithm that rapidly estimates acoustic transfer fields of a vibrating rigid object (modeled by the linear modal model). Wang [24] also proposed an integrated time-domain acoustic wavesolver to support sound rendering of a wide variety of physics-based simulation models and computer animated phenomena. Jin et al. [9] presented a novel learning-based impact sound synthesis algorithm that can handle sound synthesis for common arbitrary objects, especially dynamic generated objects, in real-time. Xu et al. [25] proposed an interactive design method for nonlinear isotropic and anisotropic damping of complex three-dimensional solids simulated using the Finite Element Method (FEM). These related sound simulation papers help us design and modify sound simulation algorithm using material parameters including density, Young's modulus, Poisson ratio, Rayleigh damping coefficient [14] as well as scanning 3D models to generate simulated knocking sound through processes of modal analysis, sound rendering, contact force impulse, etc.

For current acoustic-based material identification method, Tang et al. [20] presented a new method to capture the acoustic characteristics of real-world rooms using commodity devices, and use the captured characteristics to generate similar sounding sources with virtual models. However, they required pre-constructed virtual room geometry as input for acoustic analysis and material optimization, which does not fit our VR/AR application and capability. Ren et al. [18] introduced a novel method using prerecorded audio clips to estimate material parameters that capture the inherent quality of recorded sounding materials. However, their classification accuracy is low between some materials with similar knocking sound. Also, for our challenges including random knocking positions and new materials from users they still missed feasible solutions. These acoustic-based material identification methods, though cannot either completely meet our demand for the material identification of object with 3D model in VR/AR or well handling our challenges, they still provide a useful and meaningful idea for our system design and make a good reference.

Other than the acoustic-based material identification methods, other approaches utilized such as RF signal, pressure and deformation, etc. Wang et al. [21] introduced TagScan, a system that can identify the material type and image the horizontal cut of a target simultaneously with cheap commercial off-the-shelf (COTS) RFID devices. However, it could only identify fluid materials and compositions, which cannot meet our demands to identify solid object materials. Abdulali et al. [1] introduced a measurement-based modeling framework for hyper-elastic material identification and real-time haptic rendering. Limitation is that only hyper-elastic material can be well specified using their system, leading to low robustness when facing target object with rigid body. Although these approaches have their limitation of the target object and its material, they provide a wide view of various material identification approaches regarding the user's changing need and motivation.

6 CONCLUSION

In the research field of specifying and identifying material of an object by knocking, we proposed a new model using DANN transfer learning method. By generating simulation sound of an object by its 3D model using modal sound synthesis method, we obtain the material information of the object, which can be used to generate sound in VR scenario to improve the user experience. Although some existing research focus on how to detect an object's material by knocking, traditional methods only use pre-collected sound data to train a classifier and do not utilize the scanned 3D model, which inevitably require a large training database to achieve acceptable performance and its accuracy may drop on new models. Using example-guided methods to detect model's material, challenges appear that user may knock at different points and the simulation sound cannot fit the real sound well. Current methods have shown that the algorithms perform under expectation, while our method using DANN transfer learning method can extract domain-independent features from simulated sound and real knocking sound. The benchmark shows that our trained feature extractor can transfer our data to the same feature domain, which solves our challenges well. From overall evaluation, the performance of our model is much better than others, giving satisfying accuracy of material identification.

For future work, we will solve the problem of identifying object with new materials beyond our training set. Also, more evaluations will be given to test how the non-uniform materials, different users, different objects used when knocking and other factors affecting the system accuracy. Besides, current work shows that it is possible to estimate the position of the user's tapping, while its accuracy require further evaluation since it is harder to identify the knocking position than the material.

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