FabAuth: Printed Objects Identification Using Resonant Properties of Their Inner Structures

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ABSTRACT

We present a method we propose called FabAuth for identifying 3D-printed objects, which utilizes the differences in the resonant properties of such objects. We focus on changing the internal structures of each object made through a 3D printing process to assign a unique resonant property to it even if multiple objects have the same appearance. To identify the objects, the method identifies resonant property differences by using vibration that can pass through 3D-printed objects. The method can be applied even to low-filled 3D-printed objects as long as an acoustic wave can travel through the objects from one sensor to another. To validate the method's feasibility, we conducted a preliminary experiment to confirm whether it can be applied to low-filled 3D-printed objects and found that its average classification accuracy reached 92.2%.

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Genuineness Certification; Digital Watermark; Resonant Property; Acoustic Sensing.

INTRODUCTION

Developing digital fabrication machines such as 3D printers and lasers cutter has changed how objects are made. Simply preparing digital data for these fabrication machines enables users to easily create objects as they like, but it also enables them to make imitations. To further vitalize the digital fabrication market, it is essential to certify objects' genuineness to protect the data and makers' rights (copyrights) through the use of contrivances such as digital watermarks.

However, merely introducing easy genuineness certification methods to 3D-printed objects is not suitable for this purpose; for example, simply tagging objects with 1D barcodes [3] or 2D barcodes [1] might impede creativity because both methods impair the appearance of objects. Tag embedding into 3D-printed objects [5, 8] needs highly filled 3D-printed objects because these methods make use of air pockets in the objects. In addition, these methods are difficult to apply to complex 3D-printed objects. For these reasons, digital watermarks of 3D-printed objects should be usable regardless of complexity, materials, and filling rate, all of which are factors that might impede creativity in 3D printing.

To address these issues, we here present a method we propose called FabAuth for identifying 3D-printed objects, which utilizes the differences in the resonant properties of objects. The resonant properties change along with the combinative conditions of shapes, boundary conditions, and materials. We focus on changing the internal structures of objects so that we can assign a unique resonant property to each object even if two or more objects have the same appearance. To avoid acoustic attenuation except for passing through the objects, FabAuth identifies the resonant property differences by using vibration measured by piezo elements in contact with 3D-printed objects with active acoustic sensing, which can pass through the objects without drastic attenuation. To initially investigate the performance of our proposed method, we conducted a preliminary experiment to confirm whether it can be applied to 3D-printed objects with a low filling rate.

RELATED WORK

Embedding tags into 3D-printed objects together with recognizing them is one of the most closely related approaches to ours. For example, AirCode [5] is a computer imaging-based tag embedding technique that utilizes air pockets under the surfaces of opaque 3D-printed objects. Note that AirCode assumes that the target objects are homogeneously printed by semitransparent materials. InfraStructs [8] embeds passive tags by utilizing internal spaces of 3D-printed objects and recognizes them by using terahertz imaging, which requires excessively expensive equipment. These methods need highly filled 3D-printed objects to embed tags into their internal space. However, since there are likely to be several low-filled 3D-printed objects in the field we assume, we should strive to develop an identification method that can be applied to any 3D-printed object regardless of its filling rate.

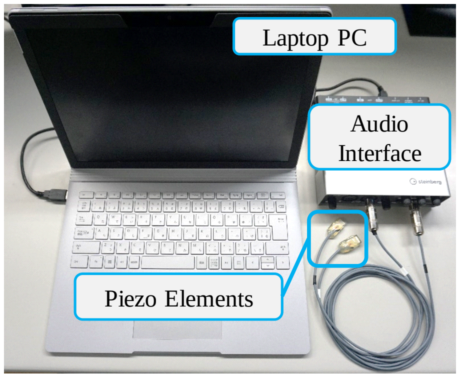

Figure 1: System overview.

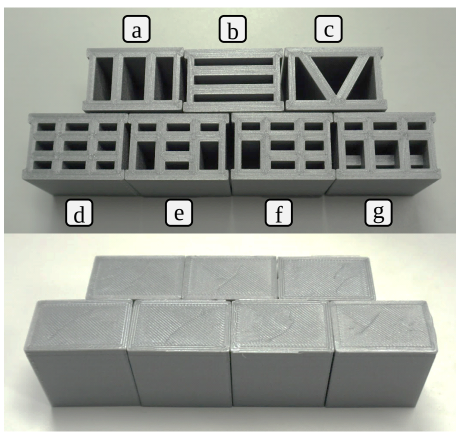

Figure 2: 3D-printed objects with different inner-structures.

We therefore focus on frequency resonance sensing for 3D-printed objects which have been used in the HCI fieild [4, 7].

FABAUTH

Our proposed object identification method, FabAuth, consists of 3D-printed objects with an arbitrary inner structure made through a 3D printing process and a system for identifying them using active acoustic sensing.

3D-printed Objects with Unique Internal Structures

All objects have their own resonant properties based on their resonant modes, natural frequency, and modal damping, all of which are affected by the objects' shapes, materials, and boundary conditions. We focus on the fact that shapes and boundary conditions can change resonant properties. Using the primal requirements for 3D-printed object identification, we tried to change the resonant properties of objects by changing their inner structure and identify the objects on the basis of their resonant properties.

Acoustic-based Identification System

To measure the resonant properties appearing in an acoustic frequency spectrum that suffice for 3D-printed object identification while suppressing acoustic attenuation, we employed active acoustic sensing which focuses on vibration measured by piezo elements in contact with 3D-printed objects. To vibrate 3D-printed objects with sufficient power, we employed piezo elements with a bimorph structure, which is the same as previously reported [6]. Our identification system consists of a laptop PC, a USB audio interface, and a pair of piezo elements for acoustic sensing. We focus on the fact that piezo elements can convert vibrations to electricity and vice versa, and employ a pair of piezo elements. One vibrates a target object from an arbitrary position and the other measures the vibration passed through the object from another position to analyze the acoustic frequency spectrum. Acoustic signals from/to piezo elements are amplified via the USB audio interface. We analyzed the objects' resonant properties using the signals and then identified the objects by machine learning.

PRELIMINARY EVALUATION

To show proof-of-concept (PoC) of FabAuth, we evaluated whether the method can classify seven fabricated objects as shown in Figure 2. We printed these objects by using Ultimaker 2+ with plastic (PLA) filaments at the filling rate of 20%.

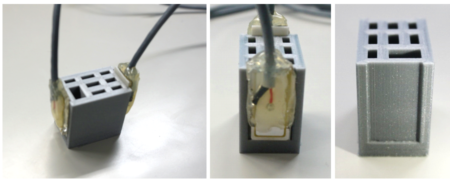

Figure 3: Overview of data measurement with attaching a pair of piezo elements.

Experimental Conditions

For the preliminary evaluation, we implemented an acoustic-based identification system. We used bimorph piezo elements (K2512BP1, THRIVE) for both acoustic waves transmission and the object-through acoustic response measurement. To avoid acousitc attenuation except for passing through the objects, we attached a pair of piezo elements to target objects with double-sided tapes; one for signal emission and the other for signal receiving. The current signals from/to the piezo elements were amplified and connected to a computer (OS: Windows10 64bit, CPU: Intel Core i7 1.9GHz, RAM: 16GB) via the USB audio interface (UR22mkII, Steinberg).

Vibration Input. We programmed a signal generator to generate sweep signal at a 96 kHz sampling rate with frequency increasing linearly from 20 to 40 kHz within every 20 ms, whose frequency range is the same as previously reported [6]. The USB audio interface is connected to a piezo sensor that emits the signal to objects. The signal emission is repeated until the program finishes.

Vibration Measurement. An acoustic response analyzer converts the vibration measured by the receiving piezo sensor to the acoustic frequency response. The sampling rate of this vibration measurement is set at 96 kHz, the same as that of the vibration input.

Measured Vibration Analysis. To analyze the acoustic frequency, we used fast Fourier transform for 8192-point Hamming windowed data and calculated 4096 frequency spectrum data items from 0 to 48 kHz. We created 426 features for machine learning from the frequency spectrum data items. We used WEKA data mining software [2] for object identification; the classification algorithm we used was a support vector machine with polynominal kernel and default parameters in WEKA's sequential minimal optimization (SMO).

Dataset Measurement Procedure

To collect acoustic frequency data, we attached a pair of piezo sensors to target objects as shown in Figure 3. For each trial we conducted, we attached a pair of piezo elements to an object and then measured the acoustic frequency spectrum. In each experimental session, we conducted the trial fifty times for each of seven objects. We conducted three sessions and collected 1,050 samples (3 sessions $\times$ 7 objects $\times$ 50 samples).

Results

To validate our method's performance, we conducted leave-one-session-out cross-validation for all combinations; e.g., the data for session 1 was used as test data and the data for sessions 2 and 3 was used as training data to construct a machine learning model. The results showed that the average classification accuracy reached 92.2% (SD = 13.5), indicating that the method has the potential to

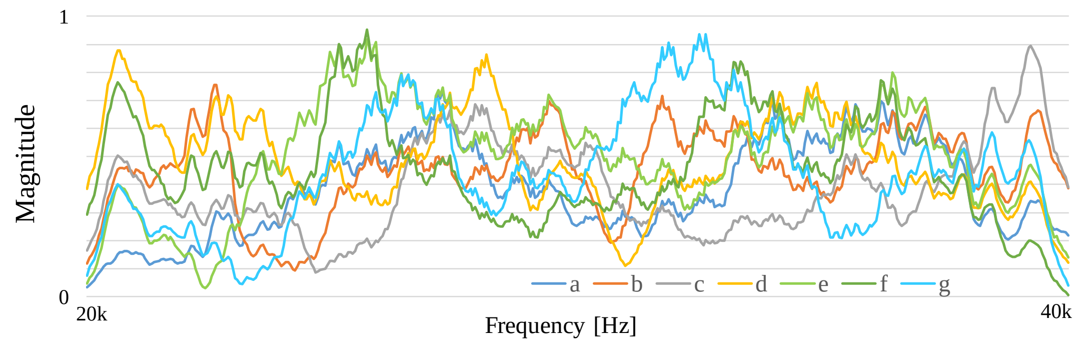

Figure 4: Averaged acoustic frequency spectrum of each object in the preliminary experiment. Each line means the average of all measured data in each object (average of 150 samples/object). Y axix's values means min-max normalized magnitude of power spectrum.

Table 1: Confusion matrix of the overall results.

Predicted Results

Actual Results	a	b	c	d	e	f	g
a	100.0	0.0	0.0	0.0	0.0	0.0	0.0
b	0.0	70.7	29.3	0.0	0.0	0.0	0.0
c	0.0	18.0	74.7	7.3	0.0	0.0	0.0
d	0.0	0.0	0.0	100.0	0.0	0.0	0.0
e	0.0	0.0	0.0	0.0	100.0	0.0	0.0
f	0.0	0.0	0.0	0.0	0.0	100.0	0.0
g	0.0	0.0	0.0	0.0	0.0	0.0	100.0

classify seven objects (Table 1). The example of acoustic frequency spectrum of all objects is shown in Figure 4, and Figure 5 shows an example of the acoustic frequency spectrum of each session targeting object shown as "g" in Figure 2.

DISCUSSION

To show the PoC of our FabAuth method, we conducted a preliminary evaluation and confirmed that it was able to identify seven rectangular objects in this study. Many 3D-printed objects will be placed on the ground so that the bottom face is a blind spot that users cannot see. By designing the internal structure of 3D-printed objects and attaching a pair of piezo sensors to this blind spot, the method can be applied without visibly damaging the appearance.

Since FabAuth only uses internal structures of 3D-printed objects, we believe that it can mitigate prerequisites in terms of structure complexity, materials, and filling rate. To show the method's further potential, we plan to ascertain the relationship between identification accuracy and printing conditions such as different materials, filling rate, complexity of structures, size of internal structures, or other conditions including time degradation. In addition, we should also clarify the limitations and possibilities of FabAuth considering the number of identifiable objects and acoustic signal measurement condition such as effects of external stimulus derived from the attachments for piezo elements placement or an interfere finger touching the objects. We should as well confirm whether there is any regularity between inner structure patterns and their acoustic resonance.

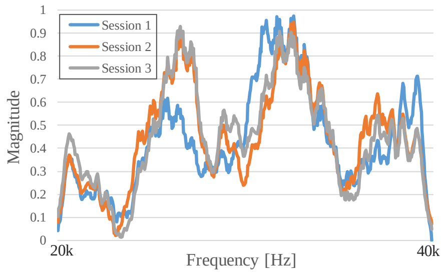

Figure 5: Example of averaged acoustic frequency spectrum of each session targeting object (shown as "g" in Figure 2). Each line means the average of all measured data in each session (average of 50 samples). Y axix's values means min-max normalized magnitude of power spectrum.

However, the method in its current form may have limitations with respect to sensor placements; it needs to obtain approximately the same acoustic characteristics to be effective, but acoustic characteristics may change depending where a pair of piezo elements is located. Our future plans include ascertaining how the location affects identification accuracy.

CONCLUSION

We have presented a method we propose for identifying 3D-printed objects. This method, called FabAuth, utilizes differences in the resonant properties of 3D-printed objects. We focus on changing the internal structures of objects so that a unique resonant property can be assigned to each object even if two or more objects have the same appearance. A preliminary experiment showed that FabAuth can be applied to low-filled 3D-printed objects. Since the method only uses internal structures of 3D-printed objects, we believe that it can mitigate prerequisites in terms of structure complexity, materials, and filling rate. In the future, we plan to ascertain the relationship between identification accuracy and printing conditions such as different materials, filling rate, complexity of structures, size of internal structures, or other conditions including time degradation to confirm the method's further potential.

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