Acoustic Resonance Sensing for Game Controller

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***Abstract*—Gaming controllers often demand rapid, precise inputs on small, closely spaced buttons and joysticks, making them especially difficult to operate for users with limited fine-motor skills. To address this, we develop a gaming controller with a palm-sized, soft-top surface that deforms upon touch. Our controller utilizes acoustic resonance sensing via an embedded speaker and microphone, which analyze acoustic signal changes within the controller cavity to detect touch location and pressure on the deformable surface. The challenge is that a symmetric internal controller geometry can lead to ambiguities in the resonant response, as touches at mirrored positions often produce similar signals. To overcome this, we design a novel asymmetric internal structure that increases the spatial diversity and encodes a unique acoustic response. We develop a real-time signal processing and machine learning pipeline on a smartphone to classify 5 distinct touch positions with an accuracy of 98.7% and spatial error of 4.5 mm root mean square error (RMSE). The system also distinguishes between 3 pressure levels with 98.3% accuracy.**

Index Terms— Acoustic resonance sensing, tactile input, game controller, machine learning, randomized internal structures.

I. Introduction

Interacting with computing devices via keyboards, mice, gaming controllers and touchscreens can be challenging for individuals with fine motor impairments, often leading to inaccurate, accidental, or delayed inputs [1], [2]. This is because these tactile interfaces usually rely on small, tightly spaced buttons or touch targets that require precise coordination and firm presses [2]. However, users with dexterity impairments often find broad, planar surfaces easier to press, and benefit from tactile feedback and a sense of physical agency [1], [3]. Existing accessibility devices include adaptive gaming controllers such as the Xbox adaptive controller [4], which enables users to connect large buttons and input surfaces tailored to their needs. Other solutions aim to reduce tremor-induced false inputs using wearable haptic devices or non-wearable interfaces such as buttons, touch panels, or specialized mice [3], [5]. All of these devices often struggle to adapt to individual users, integrate seamlessly into a gaming setup, or support diverse control schemes used across video games.

While traditional tactile sensors rely on capacitive or resistive sensing methods [6] to measure force and pressure, acoustic sensing has emerged as a promising alternative [7]. Typically, acoustic sensing methods involve transmitting a signal within the sensing device or surrounding environment, capturing acoustic changes during touch input (on the sensing surface), and utilizing signal processing algorithms, machine learning (ML) techniques, or both, to estimate the contact locations [8]. Prior work on acoustic sensing can be categorized into vibration sensing and acoustic resonance sensing. The former method involves generating surface vibrations and measuring their response to touch or contact [9]–[14]. The latter transmits an acoustic signal within a closed space and analyzes its acoustic response changes during surface contact. Here, we focus on resonance sensors, which generally take the form of a soft tube for 1-D linear sensing [7], [15]–[20], or a planar, elastic sensing surface for 2-D sensing [8], [21]–[23]. To the best of our knowledge, acoustic tactile sensing has not been utilized in gaming controllers to improve accessibility.

This work uniquely applies acoustic resonance-based sensing to a game controller, expanding its use beyond prior applications. We present a soft and adaptable game controller featuring a hollow controller case with a soft-top sensing surface. A challenge in our approach is that symmetric internal controller geometry can lead to ambiguous signals, as mirrored touch positions often produce similar acoustic responses. To address this, we introduce a novel asymmetric internal structure that enhances location-specific acoustic signatures, which is an original contribution to acoustic tactile sensing. The system leverages acoustic resonance-based sensing via an embedded speaker and microphone, which measure frequency response changes of the controller's internal cavity as the soft surface is pressed. Our design supports ad hoc haptic interfaces ranging from touch-pad to button-like inputs, allowing the interface to adapt to the individual nature of a user's finger dexterity. This study focuses on sensor design and its technical feasibility, with accessibility as a direction for future work.

II. System design

Our 2-D touch sensor maps the internal frequency response profile within the game controller to the contact position of the user input. The sensing system consists of three major components: the controller hardware, a smartphone app that performs signal processing and runs an ML model, and a Python server on a PC that translates the ML predictions into PC input commands.

The entire tactile sensing pipeline is shown in Fig. 1. The sensing process begins by transmitting an acoustic signal into the interior space of the controller, generating resonance within the enclosed cavity and producing a unique frequency domain curve. When the sensor surface is pressed, the geometry of the cavity is altered, which changes its acoustic response and frequency profile. We assume that the Fast Fourier Transform

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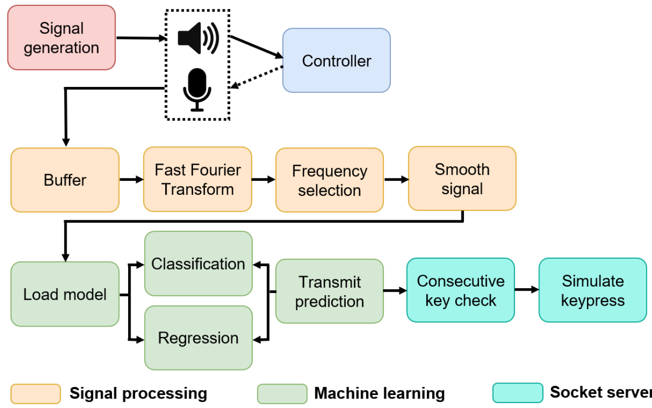


Fig. 1: Tactile sensing pipeline for contact point estimation and key press simulation.

(FFT) of the controller's internal acoustics is distinct at different contact points [23]. Thus, each contact point can be characterized by its corresponding FFT array.

A. Signal Processing Pipeline

In our design, we transmit Gaussian pulses at a repetition frequency of 20 Hz, with the high-level duration of each pulse lasting 15.8 ms. This signal produces a range of frequencies to characterize changes within the structure of the controller. As a speaker plays the transmitted signal inside the controller, a microphone captures the resulting acoustics and streams data to a connected smartphone at a 48 kHz sampling rate. The smartphone app then processes the audio to generate a feature vector to characterize the frequency response. It segments the audio into 64 ms windows and computes the FFT for each segment. To reduce data dimensionality and focus on the frequency range most affected by touch, the 7–16 kHz band is selected, reducing the FFT array from 3072 to 576 values. Finally, a moving average filter with a window size of 12 is applied to smooth the frequency spectrum, remove spikes, and enhance the robustness and consistency of the ML feature set.

B. ML Model Design

We trained three ML model systems to analyze frequency domain data, identify different contact points and properties, and explore discrete "button-style" and continuous "touch bar-style" input. All models used the FFT array as the input feature vector. First, a classification model was designed to emulate a five-button directional pad, with one central point and four surrounding points at the cardinal directions. It used five labels for the button locations and a sixth label for the unpressed state. Second, we trained a pressure classification model to distinguish among four pressure levels at a single contact point: no press, light, medium, and hard, as determined by the experimenter. Both classification models used a Support Vector Machine (SVM) with a linear kernel. Third, we developed an ensemble of models that conducted one-dimensional horizontal position tracking, with regression analysis. In this setup, the sensing surface was treated as a continuous horizontal bar located at the center. Because a regression model alone could not differentiate between pressed and unpressed states, we employed a two-stage approach: a classifier first detected whether a press occurred, and if so, the data was passed to the regressor for position estimation.

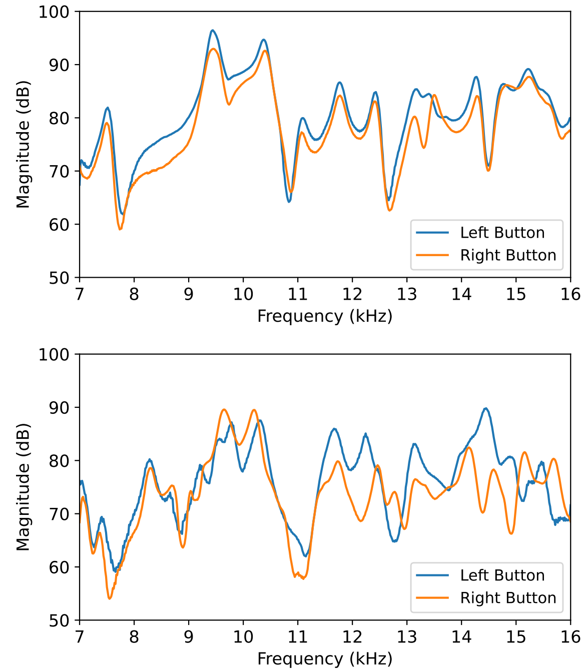
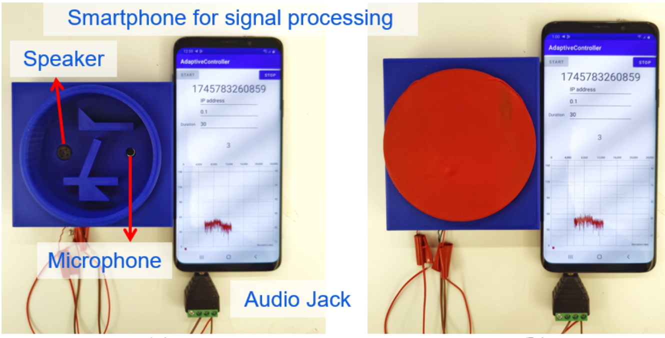


Fig. 2: FFTs at symmetrical contact points before (top) and after (bottom) introducing internal structures.

III. Implementation

Initially, we designed the controller case as a hollow cylinder embedded inside a solid rectangular prism. With this version of the controller, we found that the ML model was accurate when tested on pre-recorded data, yet performed significantly worse during real-time use. It was observed that FFT graphs appeared highly similar at contact points equidistant from a central axis, suggesting that the empty interior of the controller had introduced a "symmetry" in the frequency profile. This likely led to overfitting, which explained the model's strong asynchronous performance but weak real-time generalization. To address this issue, we introduced novel, randomized internal structures inside the controller. This successfully increased the spatial diversity, asymmetry, and distinctiveness of the frequency profiles, as shown in Fig. 2. In the figure, "Left Button" and "Right Button" indicate the FFTs corresponding to two contact points in opposite directions.

Then, we 3-D printed the game controller case with random structures (base dimensions of 9 $\times$ 10 cm). A balloon was stretched over the controller's cylindrical opening to serve as the sensing surface (see Fig. 3). A miniature speaker and microphone were embedded on the bottom of the controller. We selected a Fielect mini speaker as the transmitter and a CMC 6027 electret condenser microphone as the receiver. A CERRXIAN headphone adapter interfaced the microphone's wires to the smartphone audio port. A smartphone app was created for processing training data. Upon a button press,



(a) **(b)**

Fig. 3: Components of the controller hardware system: **(a)** Interior structure of the game controller, audio components, and smartphone app. **(b)** Covered game controller (with red balloon as the sensing surface) and smartphone app.

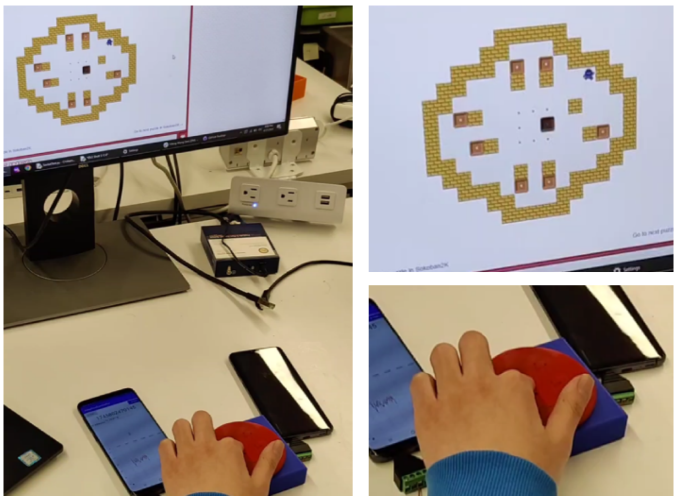


Fig. 4: Demonstration of the game controller (clockwise, starting from left): view of entire system, close-up of computer screen, and close-up of user interacting with controller.

the app would measure the acoustic response and save the FFT data to a text file, which allowed for the rapid capture of training data. We developed another smartphone app that allowed users to select an ML model and enter the IP address of the target PC. Trained models were exported in ONNX format and stored in the app's assets folder. The complete controller and smartphone setup is shown in Fig. 3 and Fig. 4. At runtime, the app performed real-time signal processing, applied the selected model, and streamed predictions via socket to a Python server on the PC. The server mapped each prediction to a keybinding and simulated key presses.

IV. Results

For discrete button classification, we achieved a high classification accuracy of 98.7% in identifying which button was pressed, using a training set of 120 instances. Fig. 5 (left) illustrates the model's performance. In this matrix, labels correspond as follows: 1 - Left, 2 - Up, 3 - Right, 4 - Down, 5 - Center, and 6 - Unpressed. This classifier also demonstrated effective real-time performance during PC gameplay (illustrated in Fig. 4). We attribute this real-time success to hardware design enhancements, particularly the addition of random asymmetric structures to the bottom of the cylinder. These modifications effectively differentiated symmetrical points, such as positions 2 and 4 or 1 and 3.

We extended our experiments to classifying varying pressure levels on the D-pad. Focusing on the central point, we defined three pressure levels: 1 - Light, 2 - Medium, and 3 - Hard. An additional label, 4, represented the unpressed state. The training set had 120 instances. The classifier achieved a high accuracy of 98.3% (Fig. 5, right). For the touch-bar regression model, the size of the training set is 240. The regression performance is shown in Fig. 6. The RMSE was calculated to be 4.5 mm. This low error enabled continuous detection of contact points along the touch bar, with high accuracy.

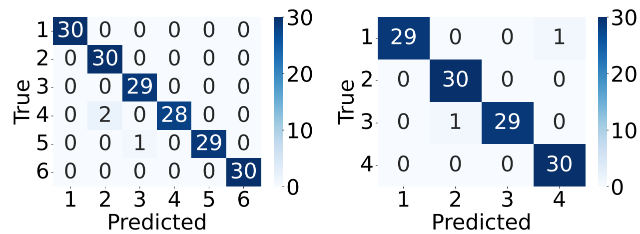


Fig. 5: Confusion matrix for the discrete button model (left) and discrete press model (right).

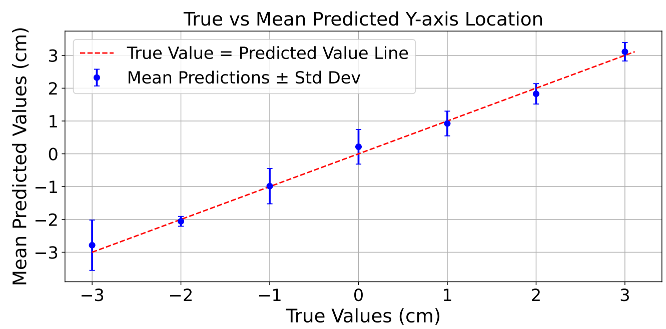


Fig. 6: Regression performance plot.

V. Conclusion

This study demonstrates the feasibility and effectiveness of using acoustic resonance sensing for a gaming controller. By integrating a soft surface, real-time signal processing, and machine learning models, the controller system accurately detects discrete button presses and continuous touch positions. The novel application of random structures to the controller enhanced internal asymmetry, and contributed to high classification accuracy and low regression error. The successful integration of the controller with PC games and its accurate real-time performance validates the system's practicality.

The controller's current size and bulkiness may limit its incorporation with accessible gaming systems. In the future, we aim to further miniaturize the sensor. In addition, we plan to conduct a user study in which individuals with fine motor impairments will test the controller in real-time gaming scenarios. Feedback and results from this study will guide refinements to the hardware form factor, improvements in model generalization, and exploration of broader applications for this acoustic sensing approach.

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