Sensing Touch Force using Active Acoustic Sensing

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ABSTRACT
We present a lightweight technique with which creators can prototype force-sensitive objects by attaching a pair of piezoelectric elements: one a vibration speaker and one a contact microphone. The key idea behind our technique is that touch force, in addition to the way the object is touched, can also be observed as different resonant frequency spectra. We also show that recognition of a touch and estimation of the touch force can be implemented by using the combination of support vector classification (SVC) and support vector regression (SVR). An experiment with an additional pressure sensor revealed that our technique might perform well in estimating touch force. We also show a tool for machine learning based on our technique that uses an animated guide, allowing creators to give the system both the training data and the labels for training machine learning needed for dealing with continuous-valued output such as SVR.

Author Keywords
Prototyping; pressure; tangential force; acoustic classification; tangibles; machine learning; support vector machine; support vector classification; support vector regression; piezoelectric sensor.

ACM Classification Keywords
H.5.2 [Information interfaces and presentation]: User Interfaces - Graphical user interfaces; Input devices & strategies.

INTRODUCTION
While techniques for prototyping touch-sensitive objects such as [6, 17, 13, 8, 3, 14] give creators the chance to prototype objects with touch interaction including grasp, the capability of sensing touch force, e.g., pressure and tangential force, will further enrich the vocabulary of touch interaction, allowing creators to prototype objects with a rich set of touch interactions.

In this paper, we explore a lightweight technique with which creators can prototype force-sensitive objects by attaching a pair of piezoelectric elements, one a vibration speaker and one a contact microphone. This technique is based on our active acoustic sensing [14], which is a technique to make existing objects touch-sensitive. The previous technique utilizes the fact that the resonant property of a solid object is sensitive to the way the object is touched; that is, the resonant property changes depending on how the object is touched. Since these changes are observed as different resonant frequency spectra, it is possible to estimate how the object is touched by analyzing the spectra.

The key idea behind our technique is that touch force, in addition to the way the object is touched, can also be observed as different resonant frequency spectra. More specifically, we utilize the fact that strengthening/weakening a touch to a solid object smoothly changes the spectra. Therefore, observing how the spectra changes in real-time can be done to estimate how the object is touched and even the touch force. In this paper, we show that recognition of a touch and estimation of the touch force can be implemented by using the combination of support vector classification (SVC) and support vector regression (SVR).

RELATED WORK
To enrich the vocabulary of touch interaction on surfaces such as touchpads and touchscreens, various attempts have been made to form force-sensitive surfaces.

Resenberg et al. used a matrix of force-variable resistors to build UnMousePad [16], which is a pressure-sensitive flexible multi-touch touchpad. Such a matrix had been used to build a thin flexible pressure sensor [11]. Rendel et al.'s PyzoFlex [15] used a ferroelectric material to form a pressure-sensitive bendable surface, which can sense even hovering interaction. While these devices can perform a wide range of stable pressure-sensing on surfaces, the sensitive area is the devices themselves. In contrast, our technique makes the surface of an object touch- and force-sensitive.

A vision-based technique was also devised. RetroDepth by Kim et al. [9] used a stereo camera and retro-reflective surfaces to precisely estimate the 3D contours of interacting objects on and above the surfaces; the precision is so high that subtle changes in the 3D locations of fingertips can be identified when the user presses the surface of a malleable object to estimate the touch pressure. In contrast, our technique can sense touch force on solid objects.

Pressure Sensing based on Resonant Property
Sensing force on the basis of the resonant property of objects is not new; a resonant pressure sensor [1] uses a diaphragm having a variable self-resonant frequency characteristic, a drive transducer to vibrate the diaphragm, and a

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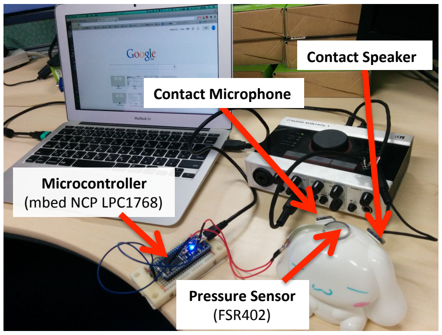

Figure 1. Experimental system. Note that pressure sensor used just for this experiment, i.e., no pressure sensor necessary in actual prototyping.

pickup transducer to capture the vibration. We use the same sensing principle to make the surface of an object touch- and force-sensitive.

Pressure Estimation using SVR

Estimating pressure by using SVR was also tried in a different context. For example, Iswandy et al. [7] used SVR to estimate the cylinder peak pressure values of three-cylinder-engines from the raw sensor data.

EXPERIMENT

To examine whether and how the idea described in INTRODUCTION works, we built an experimental system, shown in Figure 1. Note that the pressure sensor in this system was used just for this experiment, i.e., no pressure sensor is necessary in actual prototyping and only attaching a pair of piezoelectric elements is enough to sense both touch and the touch force.

Experimental System

The experimental system consists of two modules: a module for observing the resonant frequency spectra by using active acoustic sensing and a module for machine learning to recognize touch and estimate touch force.

Observing resonant frequency spectra by using active acoustic sensing

This module is almost identical to the one used in [14]. It consists of a pair of piezoelectric elements (one a vibration speaker and one a contact microphone) and a computer running software for signal processing.

As the two piezoelectric elements, we used a bimorph piezoelectric element (THRIVE K2512BP1, 25 mm $\times$ 12 mm $\times$ 0.23 mm) by cutting it into halves to reduce the footprints. Both elements were attached to an object by using double-sided adhesive bonding tape (3M SPG-12). The signals current to/from the elements were amplified and connected to a computer (Apple MacBook Air, CPU: Intel Core i7 1.7 GHz, RAM: 8 GB) via an USB audio interface (Native Instruments Audio Kontrol 1).

The computer plays sinusoid sweep signals repeatedly from 20 kHz to 40 kHz, whose frequency increases linearly in 20 ms, at a 96-kHz sampling rate through the speaker. In parallel, the computer also converts the signal captured from the microphone into the resonant frequency response by using FFT.

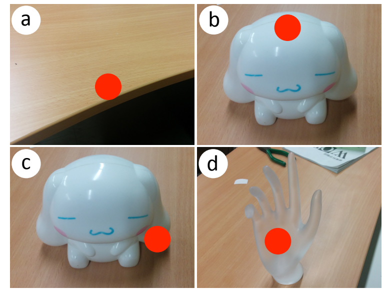

Figure 2. Conditions tested in our experiment: a) wood desk, b) head of plastic toy, c) right hand of plastic toy, and d) acrylic object. Red circle in each figure represents place where pressure sensor was attached.

Machine learning to classify touches and recognize their force

This module recognizes a touch and estimates its force in real-time by using the combination of SVC and SVR. The recognition consists of two stages. At the first stage, the module uses a SVC classifier to identify the current touch among the trained set of touches by using a SVC model, given that the model is trained beforehand. The module then uses the classification result to select one SVR model, which corresponds to the identified touch. At the second stage, the module uses a SVR classifier to recognize the touch force by using the selected SVR model.

Therefore, if a creator wants to make her/his force-sensitive prototype to recognize n kinds of touches, the creator first attaches the pair of piezoelectric elements and then touches the prototype with each kind of touch with various levels of force. As the result of this training, the module has one SVC model and n SVR models.

We implemented this module by using the C-SVC and ϵ-SVR of LIBSVM [2]. In our current implementation, we used the RBF kernel with its default parameters as a kernel function for SVC and the default parameters of ϵ-SVR. The 400-point features extracted by using FFT were passed to these algorithms every 20 ms.

In addition to the sensor necessary in prototyping, we used a pressure sensor (Interlink FSR402, 0.45-mm thick, 12 mm in diameter) for this experiment. The aim of using the pressure sensor was to systematically label the resonant frequency response according to the touch force. That is, to train a SVR model, we used the value from the pressure sensor as the label of the force. This enabled us to measure how accurately the SVR can estimate touch force. In our implementation, the value of the pressure sensor was transmitted to the computer by using a microcontroller (NXP Semiconductors, mbed NCP LPC1768) via USB as an integer ranging from 0 to 99, which means the maximum value that the pressure sensor can sense.

Setup

We tested our technique under the four conditions by using the three objects illustrated in Figure 2. The plastic toy was hollow (1.5-mm thickness), and the other ones were non-

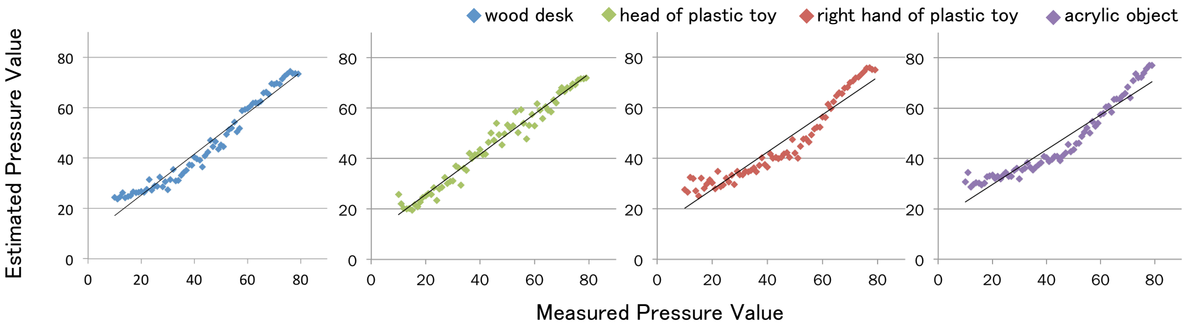

Figure 3. Results: a) wood desk, b) head of plastic toy, c) right hand of plastic toy, and d) acrylic object.

hollow. The plastic toy and the acrylic object were fixed to the desk with double sided tape so that they did not move by touch. For each condition, we attached the pressure sensor at the place annotated with a red circle, and the experimenter, i.e., the first author, touched there with the index finger during this experiment.

For each condition, we trained the classifiers first; the experimenter touched the sensor with a finger, continued the touch while varying the touch force, and detached the finger from the sensor. At the same time, the experimental system collected 10 samples of resonant frequency response for each touch force ranging from 10 to 79, i.e., 700 samples in total in each condition, to train the classifiers. We used the range because the values under 10 were unstable (even gently touching the objects with minimum pressure generates values over 9) and because values over 79 were not observed even if we pushed the pressure sensor strongly under all conditions.

Results and Discussion

Figure 3 shows the results; each subfigure is a scatter plot for each condition with a regression line, where each plot represents the mean of estimated pressure values for a measured value by 10-fold cross-validation. As the regression lines indicate, our technique shows good performance in estimating touch force.

To measure the accuracy of our technique, we also calculated the root mean square error (RMSE) between the estimated pressure values with the measured pressure values and its coefficient of determination (r^2). The result was consistent with the above observation that all these conditions exhibit strong correlations. The r^2 values ranged from 0.833 to 0.869; the RMSE ranged 7.441 to 8.704.

Although the number of tested conditions was four, these results suggest that our technique might perform well in estimating touch force. Moreover, while we used the default parameters of the SVR classifier in this experiment, the accuracy will be improved by tuning the parameters through a grid search.

TOOL FOR PROTOTYPING WITH ANIMATED GUIDE

We also designed a tool for machine learning for our technique, as shown in Figure 4. One challenging goal in designing a system for prototyping based on machine learning is how to let creators give the system both the training data and labels easily. This is especially open with a machine learning dealing with continuous-valued output such as SVR.

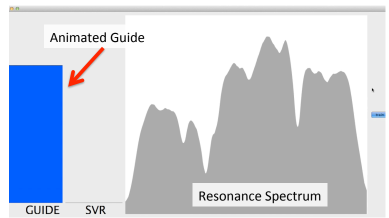

Figure 4. Tool for machine learning with animated guide. In this tool, GUIDE shows the animated guide, SVR shows the estimated force at runtime, Resonance Spectrum shows the current resonant frequency response as visual feedback.

To achieve the goal, we developed a tool that adopts an animated guide, which is the blue bar in Figure 4. This guide allows a creator to interactively give the system both a training datum, i.e., resonant frequency response, and the corresponding label, i.e., a pressure value, simultaneously. The guide begins to stretch upward once the system recognizes that the prototype is touched (this recognition is achieved by continuously comparing the difference between the resonant frequency response with that obtained when the system starts; if the difference exceeds a certain threshold which should be assigned manually in our current system, then the system recognizes that the prototype is touched). When it reaches the top of the GUI window, it disappears and appears again from the bottom of the window. The system repeats this cycle periodically, prompting the creator to perform the touch and to strengthen the touch according to the length of the guide repeatedly. Usually, repeating this cycle three or four times is enough to obtain training data. When the creator stops the animation by pressing a key, the system then begins to train the both classifiers by using the obtained data.

A great advantage of the animated guide is that it requires no pressure sensor, such as the one we used in our experiment, to train the classifiers. This allows creators to make their prototypes touch- and force-sensitive by using only a pair of two piezoelectric elements.

We tested this tool by using the same conditions illustrated in Figure 2, except that we pushed the object with an index finger at the place annotated with the red circle instead of

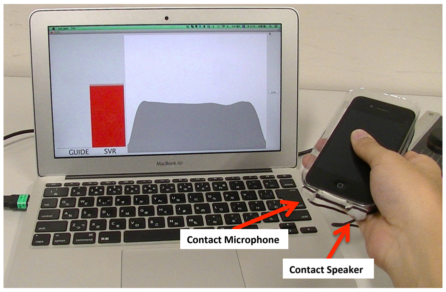

Figure 5. Prototyping smartphone with tangential force sensing.

attaching a pressure sensor. As far as we observed, the system could estimate the pressure, although the accuracy was degraded more than the results of the experiment described in the previous section.

To further test this tool, we used it to prototype a smartphone that can sense force tangential to the touchscreen, similar to [5, 10]. To do this, we attached the two piezoelectric elements to the outside of a plastic smartphone case as illustrated in Figure 5. We used a case slightly larger than the smartphone to make the case sensitive to the force exerted to it in terms of resonant frequency response. We also coated the bottom of the case with a rubber sheet to stabilize the response. Although the tangential force of this prototype is limited to be one-directional, after training, which took approximately 15 seconds, the prototype could roughly estimate the tangential force exerted onto the touchscreen in real-time.

DISCUSSION

One limitation of our technique is that it requires objects to be solid, such as the ones used in our experiment, as this approach utilizes the vibration of objects. It does not work on soft objects such as cotton or gel because of the absorption of vibration, which is the same as [14]. However, our technique still works on a wide variety of objects including flexible ones and bendable ones made of plastic.

Until now, our technique works robustly to ambient noise such as the human voice in an office environment. We have observed such noise did not interfere with the recognition. However, further in-depth investigations, especially under various outdoor conditions, are necessary in future work.

CONCLUSION AND FUTURE WORK

We presented a lightweight technique with which creators can prototype force-sensitive objects by attaching only a pair of a vibration speaker and a contact microphone as a sensor. The key idea behind our technique is that touch force, in addition to the way the object is touched, can also be observed as different resonant frequency spectra. The recognition can be implemented by using the combination of SVC and SVR, whose recognition consists of two stages. We also showed a tool for machine learning based on our technique that uses an animated guide, allowing creators to give the system both the training data and the labels for training machine learning dealing with continuous-valued output.

Our future work includes refining the accuracy in force estimation. Specifically, the parameters of the kernel in SVR were default ones; these can be tuned through a grid search to improve the accuracy. Moreover, until now, we also observed that rubbing a smooth object, i.e., moving a finger on the smooth surface of the object with a constant amount of pressure, differently changes the resonant frequency response of the object from strengthening/weakening a touch to the object, even if the gestures produce no audible sound; thus, we are trying to develop an algorithm, which is different from that of Stane [12] and Scratch Input [4], to detect rubbing gestures over smooth objects on the basis of active acoustic sensing.

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