Bzzzt - When Mobile Phones Feel At Home

Susanne Stadler
University of Salzburg
ICT&S Center
Sigmund-Haffner-Gasse 18
5020 Salzburg
stadler.susi@gmail.com

Stefan Riegler
University of Salzburg
ICT&S Center
Sigmund-Haffner-Gasse 18
5020 Salzburg
Stefan.Riegler@sbg.ac.at

Stefan Hinterkörner
University of Salzburg
ICT&S Center
Sigmund-Haffner-Gasse 18
5020 Salzburg
stefan.hinterkoerner@gmail.com

All the authors contributed equally in this work.

CHI 2012, May 5–10, 2012, Austin, TX, USA.
ACM xxx-x-xxxx-xxxx-x/xx/xx.

Abstract

"I long, as does every human being, to feel at home wherever I find myself." - Maya Angelou.

We present Bzzzt, the sketching process for an application which enables your smart phone to sense its surroundings to distinguish between familiar and unknown vibes. The phone will vibrate and record the echoes with its accelerometer or microphone, analyze those echoes and distinguish if it has felt the vibrations of this particular surface before, or not. From this it could potentially recognize some kind of feeling of being at home or hominess. Basically, this paper presents a material exploration for how we potentially could come to use the accelerometer and the microphone nowadays embedded in almost all mobile phones.

Keywords

Surface, vibration, accelerometer, microphone, machine learning technique, frequency analysis

ACM Classification Keywords

H.5.m [**Information interfaces and presentation (e.g.,HCI)**]: Miscellaneous.

General Terms

Algorithms, Experimentation, Measurement, Verification

How did this process come to start?

When talking about mobile phones and how we can explore their characteristics, one of our mobile phones started vibrating on the table. Everyone stopped talking for a moment and we realized, that we reacted to the vibration, that we felt through the table, even at a distance.

The first idea which emerged was about phones communicating through hard surfaces via vibration. By that they could perhaps get to develop relationships with each other, similar to how humans develop them and understand each others' gestures. From that we thought about developing a special vibration language, and build on the details, that form meaningful relationships. Though we found out that the accelerometer of the phones we were using (an iPhone 4S, a Samsung Galaxy S and a LG Optimus) cannot reliably record any vibration faster than 50 Hz while the vibration motor creates a frequency of 170 - 250 Hz. Also we learned by trial and error that the built-in accelerometers do not measure accurate enough vibrations from other phones transmitted over a table. However the phone can analyze its own vibrations.

This did not seem to be a breakthrough at that time, but it helped us think of a surface sensing mechanism using the accelerometer. We thought of a phone that would be able to distinguish between the surfaces it is lying on. We hypothesized that the pattern of the phone's vibrations on a soft surface, like a sweater, would be different from the vibrations it would generate on a hard table. At the beginning we had different ideas about how to measure and interpret the data, and did not know if any of them would at all work. So we decided to make three different sketches/prototypes, two of them using the accelerometer and one the microphone.

Combined with the threshold of private and public (given by the call) we thought of the phone, from recognizing these vibration patterns, potentially could develop a feeling of being home, or a feeling of hominess, when being surrounded by familiar vibrations. And feeling alien on surfaces that create vibration patterns new to the phone. This is like how hominess for humans not only are the structures, the furniture and the people we are used to, but also in a way the vibration patterns we are familiar with, like living next to a train station for example. The mobile phone might not be able to roll up in front of the fireplace and purr, but it could come to communicate the good feeling after a long day finally being in its favorite loading unit. Our concept was now to make mobile phones able to detect different surfaces through their own created vibrations. Our idea was also that a phone could come to feel better on materials that have similarities in density and acoustics. To do so, the phone would have to vibrate, capture the echoes, and then determine if it knows the echoes of the surface it was put on, or if it is an echo, a surface, new to the phone.

Methodology and Related work

After an initial search we found out there is no surface detection technology through vibration available. Knowing that, we also understood how a material exploration of the vibrator not only could aid us in our project, making the phone acquire a feeling of hominess, but also it could potentially become an addition to the GPS technology, to let the phone not just know the position it is in (i.e. its longitude and latitude) but also what texture it is on. Think of when a phone is lost in the home it could potentially communicate what surface it is on, like 'soft' textile for the pocket and 'hard' textile for the table cloth. So even though we conducted this material exploration from the idea of making mobile phones communicate a

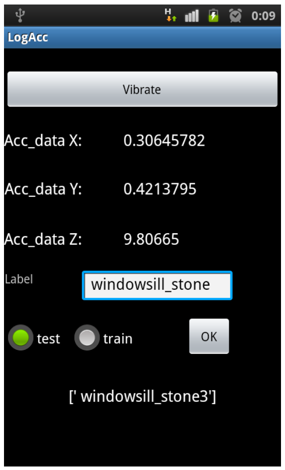

Figure 1: (Prototype one) Result of a test run where the phone has been placed after training on position three (*_stone3) and is indeed classified the right way.

feeling of hominess, we knew also that a deliverable of this project could be surface detection in general.

For the exploratory design process we took inspiration from Sundström et al.'s work on the Inspirational Bits [4]. The most important dogma, we learned from their work, was not to get stuck on the specifics of an idea before having explored its design space and what possibilities there are in various materials that could be used.

Inspiration we also found in two other papers;
First Marquardt et al. [3] described how iPhones decode vibrations from nearby keyboards using accelerometers. This showed us how sensitive mobile phone accelerometers are, and how diverse possibilities there are in what analysis and interpretations that can be done with this kind of data. From this we understood that we also had to work out what analysis methods we should come to use on the input we would get from the mobile phone accelerometers. But we had the mobile phone itself as a vibration source and not a keyboard.
Also we found inspiration in how Harrison et al. [2] describe how they used high fidelity accelerometer sensors on a wristband to detect the location of a finger tap through the vibrations traveling through the arm of a person, when tapping it.

Our Sketching process

Following the Inspirational Bits method, we started developing three prototypes (sketches) using different approaches to recognize familiar surfaces. We wanted them all on proof-of-concept level, meaning we developed them to the stage where they could be tested and felt. This is to open up the design space for what direction we would take (in this paper suggest) for a prototype aiming towards our overall design idea, of a system capable of recognizing familiar surfaces and expressing familiarity with them.

Sketch one The first sketch/prototype uses the accelerometer on a Samsung Galaxy S GT-19000 platform with Android 2.3.3. When putting the phone on a specific surface the program starts by pushing the "Vibrate" button (see Figure 1). Thereafter the phone vibrates for 4000 ms and simultaneously the built-in accelerometer measures these 4000 ms of the phone's movements (x, y, z-axis) and store this to the phone. In a second step this data can be transferred to a server. Therefore we distinguish between two modes: a "train mode" and a "test mode". In the "train mode" accelerometer data of different surfaces, which can be labeled uniquely, are collected. In the "test mode" the system recognizes a known surface. To do so, a Support Vector Machine (SVM) is used for classification. We have implemented the SVM remotely on a server, using Python and the PyML package[1]. The response of the server in the "test mode" is the label, predicted by the SVM (e.g. 'windowstill_stone'). A screenshot is depicted in Figure 1.

We have tested the prototype in two conditions. First, training and testing in one position of a single surface (C1). Second, training and testing in more positions of a single surface (C2).

Findings: C1: Our results show that the classification works pretty well. For three surfaces we reach the maximum success rate (SR) and balanced success rate (BSR) of 100 percent. As we expand the number of surface categories the misclassification increases, see Table 1. The BSR for seven surfaces is still 76.42 percent.

[1] Asa Ben-Hur. http://pyml.sourceforge.net/. Last accessed December 30, 2011.

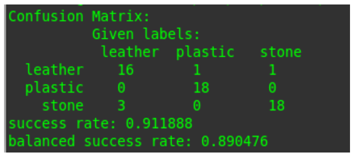

Figure 2: (Prototype one) Confusion matrix of C2. Abbr: couch (leather), toiletlid (plastic), windowsill (stone).

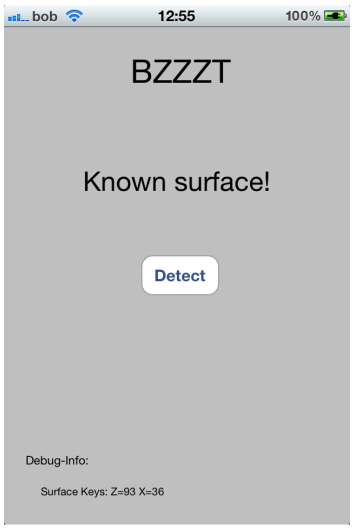

Figure 3: (Prototype two) iOS based prototype detects surface.

	3 surfaces	5 surfaces	7 surfaces
success rate	1.000000	0.960000	0.914286
balanced success rate	1.000000	0.890000	0.764286

Table 1: (Balanced) Success Rate results for tests (C1).

C2: For the second condition we also have a very good result (BSR = 0.93 percent). We have 19 datasets/surfaces and stored all positions $(P_x, 1 \leq x \leq n)$ under a unique label in the training data set (e.g. P_1: windowsill_stone1, P_2: windowsill_stone2). To simplify the table we aggregated the positions in one label. The performance of the classification algorithm can be seen in the confusion matrix (Figure 2). Each row presents the actual class and each column the predicted class. All correctly classified surfaces are located in the diagonal of the table. An interesting finding can be seen with a detailed look at the confusion matrix. In condition 1 almost no misclassification is reported. In condition 2, when the phone was put on different places on the same surface misclassification occurred.

Sketch two The second sketch/prototype software also uses the accelerometer and was built and tested on an iPhone 4S with iOS 5. The prototype first measures 5 seconds of the phone movement, without vibrating, in order to find a maximum amplitude that is not caused by phone-vibration. After that it measures another 5 seconds while vibrating and counts the number of amplitudes that surpass the predetermined maximum amplitude by more than 1 percent. This number (called peak-key) is used to find a surface-bin. A surface-bin describes a unique surface. Experiments have shown that the peak-key for hard surfaces is from 0 to 10 and the peak-key for soft surfaces is from 70 to 80. This fact lets us determine on which surface the mobile phone lies.
The iPhone can distinguish between different surfaces, but cannot recognize if the surface is wood or cardboard. If the prototype detects a known surface the third time, the user interface will tell you, that it knows the current surface (Figure 3).

We tested the prototype on a wooden table and on an empty card box. These are very different sounding surfaces and so the peak-keys are well separated. We made 20 surface detections on each surface and used the x-axis data of the accelerometer. After that, we used the z-axis instead of the x-axis, to find the axis with the best usable outcomes.

Findings: The test results showed that only the z-axis of the accelerometer delivers useful data. Using the z-axis data we had a detection rate of 80 percent on the wood table, respectively 60 percent on the cardboard. So the iPhone sketch/prototype is able to detect different surfaces. The hollower the sound of the surface is, the higher the error rate becomes. This high error rates develop out of the fixed surface-bin sizes. When the surface sounds hollower a bigger peak-key is calculated, which often jumps out of its assigned surface-bin.

Sketch three Contrary to the other sketches/prototypes, this one uses the microphone of the mobile device. It was developed on an LG Optimus 2x P990 running Android 2.3.4. It records 1000 ms of sound while vibrating. To determine the strength of upper tone frequencies caused by the vibration-motor the Goerzel algorithm [1] was used. When given an audio recording, or any other kind of signal, this algorithm can determine how strong a certain frequency is present in the sample. The measured strength of these frequencies is used to distinguish and recognize different surfaces.

We are only analyzing certain overtones of the frequency

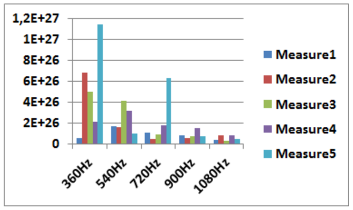

Figure 4: Presswood table, laminated.

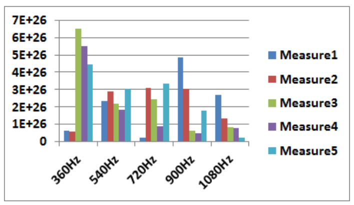

Figure 5: Envelope on a wooden table.

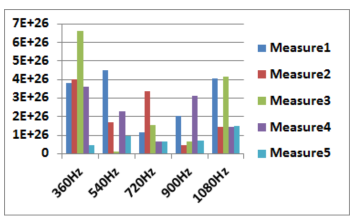

Figure 6: Glass scale.

of the vibration motor, because the other frequencies are most likely to be only background noise that is not relevant.

To enhance the result, this is done five times in a row, and the mean values are used to compare.
This prototype was only used to measure data from different surfaces to show if a classification is possible at all. The test was run in a relatively silent room, meaning there were minor background noises caused by the testing person and the ventilation of two PCs.

Figure 4, Figure 5 and Figure 6 show five detection attempts, consisting of the mean of five measurements, where every color stands for a different attempt. The figures show the output of the Goerzel algorithm, analyzing the raw data for the frequencies 180 Hz, 360 Hz, 540 Hz up to 5580 Hz in 180 Hz steps. For scaling reasons, only the frequencies from 360 Hz to 1080 Hz are plotted in these figures. The 180 Hz value was simply too high, so the differences between the other frequencies would not have been visible to the reader. One can see, that there are certain similarities, visible to the bare eye, yet there are always some frequencies out of proportion.

Findings: We found, that the microphone and the Goerzel algorithm can be used to identify the vibration patterns of surfaces. When we tested in a loud environment it was not possible to identify surfaces analyzing the data. It seems that this technique will only work in silence.

Discussion

The main problem was to recognize familiar surfaces.

Depending on the structure of the surface, different detection positions on the surface can have different characteristics. The spatial location of the phone also has an influence on the results. Additionally it is very important for all sketches to not move the phone during a measurement.

All our sketches show, that it is possible to recognize different surfaces. The second sketch is very good in differentiating between opposite surfaces (solid wood table/cardboard). An advantage is also, that it can fully run locally on the phone because it needs low computation power. The first sketch is able to distinguish more surfaces, but needs more computation power so that a server for calculation is needed. One restriction of the third sketch, which might not surprise the reader, is that it had worse results depending on the noise level around it (because it uses the microphone). That means, the louder it was around the phone the more problems it had hearing on what surface it was lying.

The used techniques are able to preprocess and classify input and distinguish between 'anything soft' and 'anything hard'. The developed surface detection techniques are accurate most of the time. Nevertheless we believe there is potential for further research in fine-tuning the surface detection, so that phones can distinguish between more surfaces without losing accuracy.

Advice for how to continue;
If choosing sketch one: We can envision a multitude of further experiments such as: What impact on the results does an expansion of surface datasets have for training? Can we use different vibration intensities? Experimenting with SVM parameter settings (use other parameters to train, e.g. FFT coefficients) may improve the result. Another step would be to consider options how to implement the classification on the smart phone itself.

If sketch two: The peak-key difference between two runs on a hollow sounding surface gets bigger. For instance, the peak-key after a first detection run on a cardboard could be 76. The second detection run on the same surface calculates a peak key of 91. A surface-bin currently has a fixed bin size of 10. In this example the phone would have detected two different surfaces. So the surface-bins must be dynamic with increasing bin size. The prototype shows that it is possible to distinguish between two physically different surfaces. More research is needed if it is possible to distinguish between more surfaces.

If sketch three: Analyzing the overtone frequencies shows great differences in the strength of each frequency in comparison with differing materials. Even little differences, like an envelope lying under the phone or not, can change the outcome dramatically.

Conclusion

We have presented an explorative material study holding three different sketches for a still hypothetic system called the Bzzzt. All sketches need more test data and more exploration to refine the techniques and the detection rate, yet all of them have promising first results. The next goal will be to try combinations of different recognition techniques and test them for enhancement. This could lead to a prototype that can reliably detect most surface materials and properties like thickness and size.

A refined detection can bring us the companion that senses if a surface feels like home, a mobile phone that when lost in a room, can tell me if its surroundings feel like the floor, like the pocket of my jacket, or like the table.

Surface detection could also potentially be used in various apps to help blind, elderly or disabled people.

New possibilities open up as we take another small step forward. This exploration of how to use the vibrator and the microphone nowadays embedded in almost all mobile phones has just begun.

Acknowledgements

We would like to thank Dr. Alexander Meschtscherjakov, DI (FH) Martin Murer, Professor Manfred Tscheligi as well as Dr. Petra Sundström for the inspiration throughout this process and the valuable comments on revising this paper.

References

[1] G. Goerzel. An algorithm for the evaluation of finite trigonometric series. *American Mathematics Monthly*, 65:34–35, January 1958.

[2] C. Harrison, D. Tan, and D. Morris. Skinput: appropriating the body as an input surface. In *Proceedings of the 28th international conference on Human factors in computing systems*, CHI '10, pages 453–462, New York, NY, USA, 2010. ACM.

[3] P. Marquardt, A. Verma, H. Carter, and P. Traynor. (sp)iPhone: decoding vibrations from nearby keyboards using mobile phone accelerometers. In *Proceedings of the 18th ACM conference on Computer and communications security*, CCS '11, pages 551–562, New York, NY, USA, 2011. ACM.

[4] P. Sundström, A. Taylor, K. Grufberg, N. Wirström, J. Solsona Belenguer, and M. Lundén. Inspirational bits: towards a shared understanding of the digital material. In *Proceedings of the 2011 annual conference on Human factors in computing systems*, CHI '11, pages 1561–1570, New York, NY, USA, 2011. ACM.