Touché: Enhancing Touch Interaction on Humans, Screens, Liquids, and Everyday Objects

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ABSTRACT

Touché proposes a novel *Swept Frequency Capacitive Sensing* technique that can not only detect a touch event, but also recognize complex configurations of the human hands and body. Such contextual information significantly enhances touch interaction in a broad range of applications, from conventional touchscreens to unique contexts and materials. For example, in our explorations we add touch and gesture sensitivity to the human body and liquids. We demonstrate the rich capabilities of *Touché* with five example setups from different application domains and conduct experimental studies that show gesture classification accuracies of 99% are achievable with our technology.

Author Keywords: Touch; gestures; ubiquitous interfaces; sensors; on-body computing; mobile devices.

ACM Classification Keywords

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

INTRODUCTION

Touché is a novel capacitive touch sensing technology that provides rich touch and gesture sensitivity to a variety of analogue and digital objects. The technology is *scalable*, i.e., the same sensor is equally effective for a pencil, a doorknob, a mobile phone or a table. Gesture recognition also scales with objects: a *Touché* enhanced doorknob can capture the configuration of fingers touching it, while a table can track the posture of the entire user (Figures 1b, 6 and 7).

Sensing with *Touché* is not limited to inanimate objects – the user's body can also be made touch and gesture sensitive (Figures 1a and 9). In general, *Touché* makes it very easy to add touch and gesture interactivity to unusual, non-solid objects and materials, such as a body of water. Using *Touché* we can recognize when users touch the water's surface or dip their fingers into it (Figures 1c and 10).

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Notably, instrumenting objects, humans and liquids with *Touché* is trivial: *a single electrode* embedded into an object and attached to our sensor controller is sufficient to computationally enhance an object with rich touch and gesture interactivity. Furthermore, in the case of conductive objects, e.g., doorknobs or a body of water, the object itself acts as an intrinsic electrode – no additional instrumentation is necessary. Finally, *Touché* is inexpensive, safe, low power and compact; it can be easily embedded or temporarily attached anywhere touch and gesture sensitivity is desired.

Touché proposes a novel form of capacitive touch sensing that we call *Swept Frequency Capacitive Sensing* (SFCS). In a typical capacitive touch sensor, a conductive object is excited by an electrical signal at a fixed frequency. The sensing circuit monitors the return signal and determines touch events by identifying changes in this signal caused by the electrical properties of the human hand touching the object [46]. In SFCS, on the other hand, we monitor the response to capacitive human touch over a *range of frequencies*. Objects excited by an electrical signal respond differently at different frequencies, therefore, the changes in

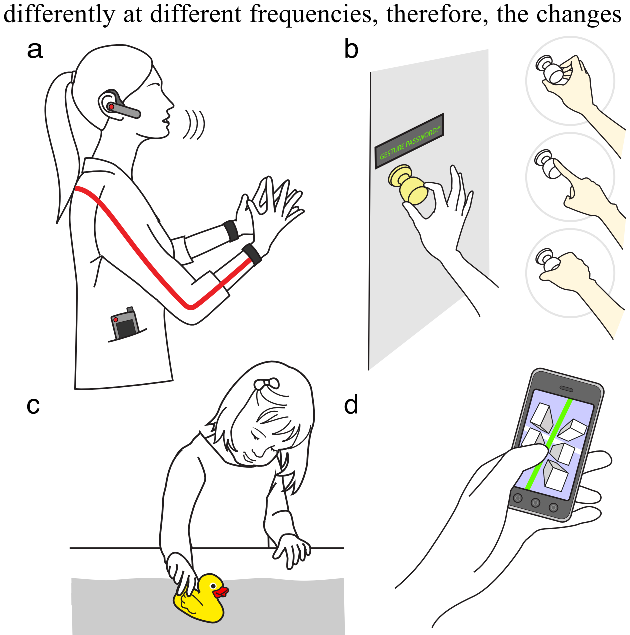


Figure 1: Touché applications: (a) on-body gesture sensing; (b) a smart doorknob with a "gesture password"; (c) interacting with water; (d) hand postures in touch screen interaction.

the return signal will also be frequency dependent. Thus, instead of measuring a *single* data point for each touch event, we measure a *multitude* of data points at different frequencies. We then use machine learning and classification techniques to demonstrate that we can reliably extract rich interaction context, such as hand or body postures, from this data. Not only can we determine that a touch event occurred, we can also determine *how* it occurred. Importantly, this contextual touch information is captured through a *single electrode*, which could be simply the object itself.

Although electromagnetic signal frequency sweeps have been used for decades in wireless communication and industrial proximity sensors [35], we are not aware of any previous attempt to explore this technique for *touch interaction*. Our contributions, therefore, are multifold:

1) We propose and develop a novel capacitive touch sensing technology, called Swept Frequency Capacitive Sensing. It allows for minimally instrumented objects to capture a wealth of information about the context of touch interaction. It also permits novel mediums for capacitive touch and gesture sensing, such as water and the human body.

2) We report a number of innovative applications that demonstrate the utility of our technology including a) smart touch interaction on everyday objects, b) tracking human body postures with a table, c) enhancing touchscreen interaction, d) making the human body touch sensitive, and e) recognizing hand gestures in liquids.

3) We conduct controlled experimental evaluations for each of the above applications. Results demonstrate recognition rates approaching 100%. This suggests *Touché* is immediately feasible in a variety of real-world applications.

RELATED WORK AND APPROACHES

The importance of touch and gestures has been long appreciated in the research and practice of human-computer interaction (HCI). There is a tremendous body of previous work related to touch, including the development of touch sensors and tactile displays, hand gesture tracking and recognition, designing interaction techniques and applications for touch, building multitouch, tangible and flexible devices. See [2, 6, 21, 24, 25, 27, 44] for a subset of previous work on touch.

The foundation for all touch interaction is touch sensing, i.e., technologies that capture human touch and gestures. This includes sensing touch using cameras or arrays of optical elements [15, 22], laser rangefinders [4], resistance and pressure sensors [31] and acoustics [16, 17] – to name a few. The most relevant technology is *capacitive touch sensing,* a family of sensing techniques based on same physical phenomenon – *capacitive coupling.*

The basic principles of operation in most common capacitive sensing techniques are quite similar: A periodic electrical signal is injected into an electrode forming an oscillating electrical field. As the user's hand approaches the electrode, a weak capacitive link is formed between the electrode and conductive physiological fluids inside the human hand, altering the signal supplied by the electrode. This happens because the user body introduces an additional path for flow of charges, acting as a charge "sink" [46]. By measuring the degree of this signal change, touch events can be detected.

There is a wide variety of capacitive touch sensing techniques. One important design variable is the choice of signal property that is used to detect touch events, e.g., changes in *signal phase* [19] or *signal amplitude* [1, 25, 30] can be used for touch detection. The signal excitation technique is another important design variable. For example, the earliest capacitive proximity sensors in the 1970s were oscillating at resonant frequency and measured signal dumping as additional capacitance that would affect the resonant frequency of the sensing circuit [35]. The choice of topology of electrode layouts, the materials used for electrodes and substrates and the specifics of signal measurement resulted in a multitude of capacitive techniques, including charge transfer, surface and projective capacitive, among others [1, 25].

Capacitive sensing is a malleable and inexpensive technology – all it requires is a simple conductive element that is easy to manufacture and integrate into devices or environments. Consequently, today we find capacitive touch in millions of consumer device controls and touch screens. It has, however, a number of limitations. One important limitation is that capacitive sensing is not particularly expressive – it can only detect when a finger is touching the device and sometimes infer finger proximity. To increase the expressiveness, matrices of electrodes are scanned to create a 2D capacitive image [6, 21, 30, 37]. Such space multiplexing allows the device to capture spatial gestures, hand profiles [30] or even rough 3D shapes [36]. However, this comes at the cost of increased engineering complexity, limiting its applications and precluding ad hoc instrumentation of our living and working spaces. Current capacitive sensors are also limited in materials they can be used with. Typically they cannot be used on the human body or liquids.

In this paper, we advocate a different approach to enhancing the expressivity of capacitive sensing – by using *frequency multiplexing*. Instead of using a single, pre-determined frequency, we sense touch by sweeping through a range of frequencies. We refer to the resulting curve as a *capacitive profile* and demonstrate its ability to expand the vocabulary of interactive touch without increasing the number of electrodes or the complexity of the sensor itself.

Importantly, our technology is not limited to a single electrode. Sensor matrices can be easily constructed and would bring many of the unique sensing dimensions described in this paper. However, in the current work, we focus on a single electrode solution, as that is the simplest – and yet allows for surprisingly rich interactions. At the same time, it is compact, inexpensive and can be easily integrated into a variety of everyday objects and real world applications.

SWEPT FREQUENCY CAPACITIVE SENSING

The human body is conductive, e.g., the average internal resistance of a human trunk is ~100 Ω [42]. Skin, on the

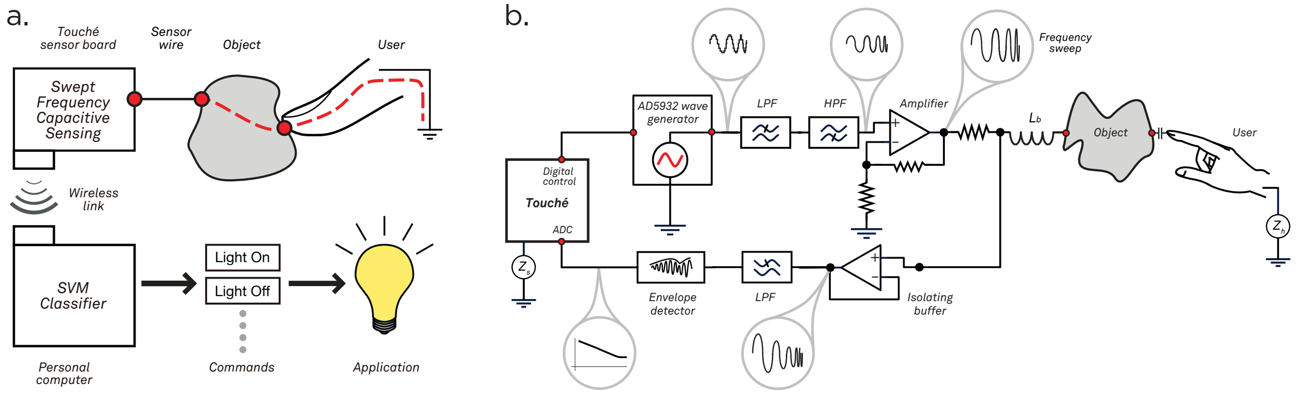


Figure 2: (a) Touché architecture (b) Swept Frequency Capacitive Sensing with Touché.

other hand, is highly resistive, ~1M Ω for dry undamaged skin [42]. This would block any weak constant electrical (DC) signal applied to the body. Alternating current (AC) signal, however, passes through the skin, which forms a capacitive interface between the electrode and ionic physiologic fluids inside the body [10]. The body forms a charge "sink" with the signal flowing though tissues and bones to ground, which is also connected to the body through a capacitive link [25, 46].

The resistive and capacitive properties of the human body oppose the applied AC signal. This opposition, or electrical *impedance*[1], changes the *phase* and *amplitude* of the AC signal. Thus, by measuring changes in the applied AC signal we can 1) detect the presence of a human body and also 2) learn about the internal composition of the body itself. This phenomenon, in its many variations, has been used since the 1960s in medical practice to measure the fluid composition of the human body [10], in electro-impedance tomography imaging [5] and even to detect the ripeness of nectarine fruits [13]. More recently, it has been used in a broad variety of capacitive touch buttons, sliders and touchscreens in human-computer interaction [6, 19, 30, 46].

The amount of signal change depends on a variety of factors. It is affected by *how a person touches the electrode*, e.g., the surface area of skin touching the electrode. It is affected by the *body's connection to ground*, e.g., wearing or not wearing shoes or having one or both feet on the ground. Finally, it strongly depends on *signal frequency*. This is because at different frequencies, the AC signal will flow through *different paths* inside of the body [10]. Indeed, just as DC signal flows through the path of least resistance, the AC signal will always flow through the path of least *impedance*. The human body is anatomically complex and different tissues, e.g., muscle, fat and bones, have different resistive and capacitive properties. As the frequency of the AC signal changes, some of the tissues become more opposed to the flow of charges, while others less, thus changing the path of the signal flow (see [10] for an overview of the bioelectrical aspects of human body impedance).

[1] Impedance is defined as a total opposition of circuit or material to AC signal at a *certain frequency*. Impedance consists of resistance and reactance, which, in case of human body, is purely capacitive [10].

Therefore, by sweeping through a range of frequencies in capacitive sensing applications, we obtain a wealth of information about 1) how the user is touching the object, 2) how the user is connected to the ground and 3) the current configuration of the human body and individual body properties. The challenge here is to reliably capture the data and then find across-user commonalities – static and temporal patterns that allow an interactive system to infer user interaction with the object, the environment, as well as the context of interaction itself.

SFCS presents an exciting opportunity to significantly expand the richness of capacitive sensing. We are not aware of previous attempts to design SFCS touch and gesture interfaces, investigate their interactive properties, identify possible application domains, or rigorously evaluate their feasibility for supporting interactive applications[2]. All relevant capacitive touch sensing techniques use a *single frequency*.

One of the reasons why SFCS techniques have not been investigated before could be due to computational expense: instead of sampling a single data point at a single frequency, SFCS requires a frequency sweep and analysis of hundreds of data points. Only recently, with the advance of fast and inexpensive microprocessors, has it become feasible to use SFCS in touch interfaces. Another challenge in using SFCS is that it requires high-frequency signals, e.g., ~3 Mhz. Designing conditioning circuitry for high-frequency signals is a complex problem. We will discuss these challenges and solutions in detail in the next section of this paper.

TOUCHÉ IMPLEMENTATION

The overall architecture of *Touché* is presented on Figure 2a. The user interacts with an object that is attached to a *Touché* sensor board via a single wire. If the object itself is conductive, the wire can be attached directly to it. Otherwise, a single electrode has to be embedded into the object and the wire attached to this electrode.

[2] We reported preliminary explorations of SFCS technology in [29].

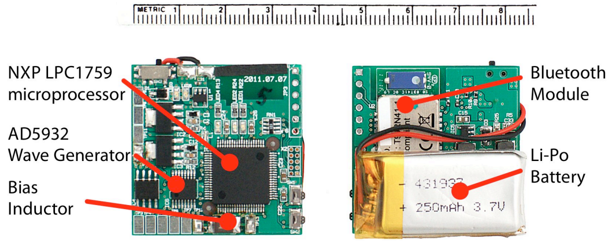


Figure 3: Touché sensing board: 36x36x5.5 mm, 13.8 grams.

Touché implements SFCS on a compact custom-built board powered by an ARM Cortex-M3 microprocessor (Figure 3). The on-board signal generator excites an electrode with sinusoid sweeps and measures returned signal at each frequency. The resulting sampled signal is a *capacitive profile* of the touch interaction. We stress that in the current version of *Touché* we do not measure phase changes of the signal in response to user interaction. We leave this for future work.

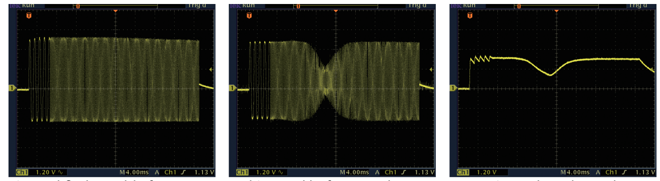
Finally, the capacitive profile is sent to a conventional computer over Bluetooth for classification. Recognized gestures can then be used to trigger different interactive functions. While it is possible to implement classification directly on the sensor board, a conventional computer provided more flexibility in fine-tuning and allowed for rapid prototyping.

Sensor board design

An ARM microprocessor, NXP LPC1759 running at 120 MHz, controls an AD5932 programmable wave generator to synthesize variable frequency sinusoidal signal sweeps from 1 KHz to 3.5 MHz in 17.5 KHz steps (i.e., 200 steps in each sweep, see Figure 2b). The signal is filtered to remove environmental noise and undesirable high frequency components and is also amplified to 6.6 Vpp (Figure 4a), which is then used to excite the attached conductive object. In the current design we tune *Touché* to sense very small variations of capacitance at lower excitation frequencies by adding a large bias inductor L_b (~100 mH), a technique used in impedance measurement. By replacing it with a bias capacitor, we can make *Touché* sensitive to very small inductive variations, e.g., copper coil stretching.

The return signal from the object is measured by adding a small sensing resistor, which converts alternating current into an alternating voltage signal (Figure 4b). This signal is then fed into a buffer to isolate sensing and excitation sections; an envelope detector then converts the AC signal into a time-varying DC signal (Figure 4c). The microprocessor samples the signal at a maximum of 200 KHz using a 12-bit analog-digital converter (ADC). A single sweep takes ~33 ms, translating to a 33 Hz update rate.

Currently, the sampling rate of ADC is a main limiting factor for speed: a dedicated ADC with a higher sampling rate would significantly increase the speed of *Touché*. Sampling is much slower at low frequencies, as it takes longer for the analogue circuitry to respond to a slowly varying signal. In applications where an object does not respond to low frequencies, we swept only in the high frequency range, tripling the sensor update rate to ~100 Hz.



a) Amplified variable frequency sinusoidal signal b) Signal before envelope c) Enveloped signal

Figure 4: Variable frequencies sweep and return signal.

Touché Sensing Configurations

There are two basic sensor configurations. First, the *user is simply touching on object or an electrode* (Figures 5a and 5c). This is the classic capacitive sensor configuration that assumes that both the sensor and the user are sharing common ground, even through different impedances. For example, if the sensor were powered from an electrical outlet, it would be connected to the ground line of a building. The user would be naturally coupled to the same ground via a capacitive link to the floor or building structure. Although this link may be weak, it is sufficient for *Touché*.

In the second case, the sensor is *touching two different locations of the user body* with its ground and signal electrodes (Figures 5b and 5d). In this configuration *Touché* measures the impedance between two body locations [10].

Communication and Recognition

For classification, we use a Support Vector Machine (SVM) implementation provided by the Weka Toolkit [12] (SMO, C=2.0, polynomial kernel, e=1.0) that runs on the aforementioned conventional computer. Each transmission from the sensor contains a 200-point capacitive profile, from which we extract a series of features for classification.

The raw impedance values from the frequency sweep have a natural high-order quality. As can be seen in Figure 6-10, the impendence profiles are highly continuous, distinctive and temporally stable. Therefore, we use all 200 values as features without any additional processing. Additionally, we compute the derivative of the impedance profile at three different levels of aliasing, by down-sampling profiles into arrays of 10, 20, 40 and using [-1, 1] kernel, yielding another 70 features. This helps to capture shape features of the

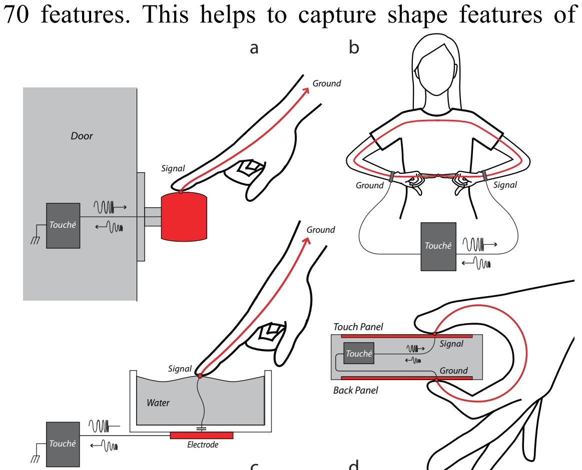


Figure 5: Configurations of *Touché* applications.

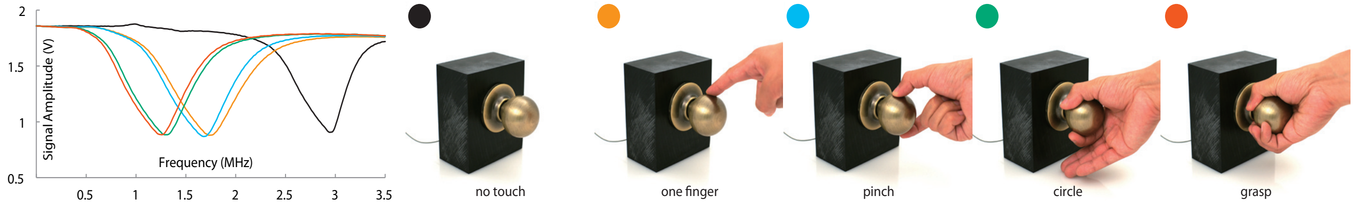


Figure 6: Capacitive profiles for making objects touch and grasp sensitive (doorknob example).

profile, independent of amplitude, e.g., it is easy to see the peaks minima in Figures 6-10 – more difficult is to see the visually subtle, but highly discriminative peak slopes. Moreover, using the derivative increases robustness to global variations in impendence, e.g., an offset of signal amplitude across all frequencies due to temperature variations. As a final feature, we include the capacitive profile minima, which was found to be highly characteristic in pilot studies (see Figures 6-10). Once the SVM has been trained, classification can proceed in a real-time fashion.

EXAMPLE TOUCHÉ APPLICATIONS

The application space of *Touché* is broad, therefore at least some categorization is pertinent to guide the development of the interfaces based on this technology. We identified five application areas where we felt that *Touché* could have the largest impact – either as a useful enhancement to an established application or a novel application, uniquely enabled by our approach:

- making *everyday objects* touch gesture sensitive
- sensing *human* bimanual hand gestures
- sensing *human* body configuration (e.g., pose)
- enhancing *traditional touch interfaces*
- sensing interaction with *unusual materials* (e.g., liquids)

In the rest of this section we propose a single exemplary application for each category, highlighting the utility and scope of our sensing approach. We then evaluate these applications experimentally in the next section of the paper.

Making objects touch and grasp sensitive

If analogue or digital objects can be made aware of how they are being touched, held or manipulated, they could configure themselves in meaningful and productive ways [14, 28, 34, 37, 38]. The canonical example is a mobile phone which, when held like a phone, operates as a phone. However, when held like a camera, the mode could switch to picture-taking automatically.

Touché offers a lightweight, non-invasive sensing approach that makes it very easy to add touch and gesture sensitivity to everyday objects. Doorknobs provide an illustrative example: they lie in our usual paths and already require touch to operate. Yet, in general, doorknobs have not been infused with computational abilities. A smart doorknob that can sense how a user is touching it could have many useful features. For example, closing a door with a tight grasp could lock it, while closing it with a pinch might set a user's away message, e.g., "back in five minutes". A sequence of grasps could constitute a "grasp password" that would allow an authorized user to unlock the door (Figure 1b).

Objects such as doorknobs can be easily instrumented with *Touché* (Figures 5a). More importantly, existing conductive structures can be used as sensing electrodes, for example, the brass surface of a doorknob. Our *Touché* sensor could be connected to these elements with a single wire, requiring no further instrumentation (Figure 6). Contrast this to previous techniques that generally require a matrix of sensors [20, 30, 37, 38]. We present detailed experimental evaluations of *Touché* in this context later in this paper.

Body Configuration Sensing

Touché can be used to sense the configuration of the entire human body. For example, a door could sense if a person is simply standing next to it, if they have raised their arm to knock on it, are pushing the door, or are leaning against it. Alternatively, a chair or a table could sense the posture of a seated person – reclined or leaning forward, arms on the armrests or not, one or two arms operating on the surface, as well as their configuration (Figure 7). More importantly, this can occur *without instrumenting* the user. Similar to everyday objects, conductive tables can be used as is, just by connecting a *Touché* sensor. Non-conductive tables would require a single flat electrode added to their surface or could simply be painted with conductive paint.

Sensing the pose of the human body without instrumenting the user has numerous compelling applications. Posture-sensing technologies are an active area of research, with applications in gaming, adaptive environments, smart offices, in-vehicle interaction, rehabilitation and many others [9]. We view *Touché* as one such enabling technology, with many exciting applications. To this end, we report an evaluation of body posture sensing with a *Touché*-enhanced table in the following Touché Evaluation section.

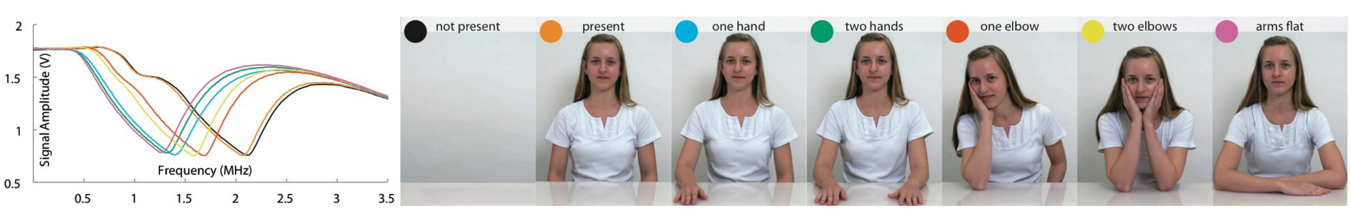


Figure 7: Capacitive profiles for sensing body postures (table examples).

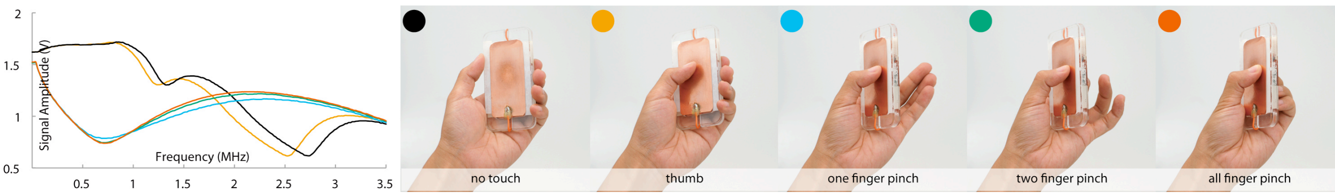


Figure 8: Capacitive profiles for enhancing touchscreen interaction with a hand posture sensing.

Enhancing Touchscreen Interaction

Touché brings new and rich interaction dimensions to conventional touch surfaces by enhancing touch with sensed *hand posture* (Figure 1d) For example, *Touché* could sense the configuration of fingers holding a device, e.g., if they are closed into a fist or held open, whether a single finger is touching, all five fingers, or the entire palm (Figures 8). The part of the hand touching could be also possibly be inferred, e.g., fingertips or knuckles, a valuable extra dimension of natural touch input [16].

These rich input dimensions are generally invisible to traditional capacitive sensing. Diffuse infrared (IR) illumination can capture touch dimensions such as finger orientation [39] and hand shape [22]. However, sensing above the surface is challenging as image quality and sensing distance is severely degraded by traditional diffuse projection surfaces ([18] offers an expensive alternative). An external tracking infrastructure can also be used. This, however, prohibits the use of mobile devices and introduces additional cost and complexity [20, 40].

Touché provides a lightweight, yet powerful, solution to bring hand posture sensing into touchscreen interaction. There are many possible implementations – one is presented in Figures 5d and 8. At the very minimum, this would enable a touch gesture similar to a mouse "right click". Right click is a standard and useful feature in desktop GUI interfaces. However, it has proved to be elusive in contemporary touch interfaces, where it is typically implemented as a tap-and-hold [16]. Additionally, combining hand pose and touch could lead to many more sophisticated interactions, such as gesture-based 3D manipulation and navigation (Figure 1d), advanced 3D sculpting and drawing, music composition and performance, among others.

In general, *Touché* could prove particularly useful for mobile touchscreen interaction, where input is constrained due to small device size. In this context, a few extra bits of input bandwidth would be a welcomed improvement. Detailed controlled experiments evaluating gesture sensing on a simulated mobile device are reported subsequently.

On-Body Gesture Sensing

Unlike inanimate physical objects, the human body is highly variable and uncontrolled, making it a particularly challenging "input device". Compounding this problem is that users are highly sensitive to instrumentation and augmentation of their bodies. For a sensing technique to be successful, it has to be minimally invasive. Research has attempted to overcome these challenges by exploring remote sensing approaches, including bio-acoustics [17], EMG [33] and computer vision [15], each of which has its own distinct set of advantages and drawbacks. *Touché* is able to sidestep much of this complexity by taking advantage of the conductive properties of the body and appropriate the skin as a touch sensitive surface while being minimally invasive.

Because humans are inherently mobile, it is advantageous to define an *on-body* signal source and charge sink for Touché. As our hands serve as our primarily means of manipulating the world, they are the most logical location to augment with *Touché*. In this case, the source or sink is placed near the hands, for example, worn like a wristwatch. The other electrode can be placed in many possible locations, including the opposite wrist (Figure 5b and 9), the waist, collar area, or lower back [11]. As a user touches different parts of their body the impedance between the electrodes varies as the signal flows through slightly different paths on and in the user's body. The resulting capacitive profile is different for each gesture, which allows us to detect a range of hand-to-hand gestures and touch locations (Figure 9).

It is worth noting the remarkable kinesthetic awareness of a human being [3], which has important implications in the design of on-body interfaces [17]. As the colloquialism "like the back of your hand" suggests, we are intimately familiar with our bodies. This can be readily demonstrated by closing one's eyes and touching our noses or clapping our hands together. In addition to our powerful kinesthetic senses, we have finely-tuned on-body touch sensations and hand-eye coordination, all of which can be leveraged for digital tasks.

A wide array of applications can be built on top of the body. One example is controlling a mobile phone using a set of

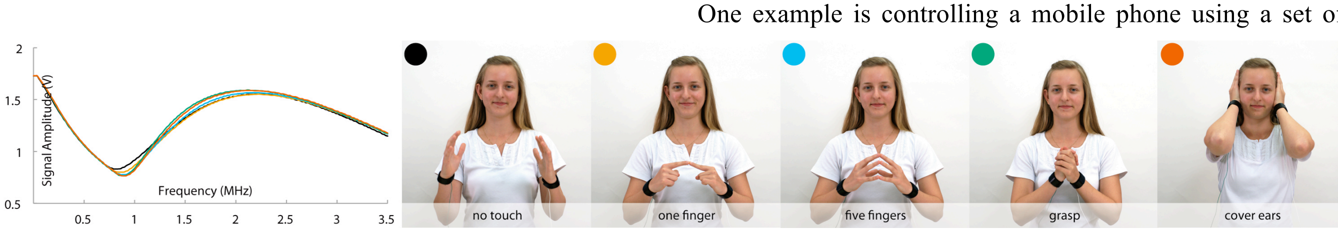


Figure 9: Capacitive profiles for on-body Sensing with wrists-mounted *Touché* sensors.

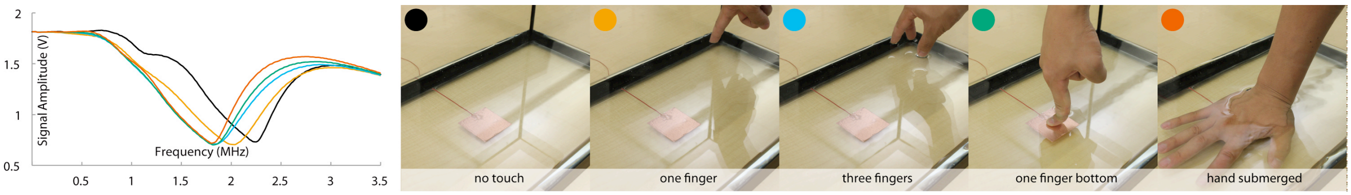


Figure 10: Capacitive profiles for interacting with water.

on-body gestures (Figure 1a). For example, making a "*shh*" gesture with index finger touching to the lips, could put the phone into silent mode. Putting the hands together, forming a book-like gesture, could replay voicemails. We evaluate feasibility of using a simple gesture set in the next section.

Sensing Gestures in Liquids

The real world does not consist only of hard and flat surfaces that can be easily enhanced with touch sensitivity. Liquid, viscous, soft and stretchable materials are important elements of everyday life. Enhancing these materials with touch sensitivity, however, is challenging. Although there is a growing body of research sensing touch for textile, paper and silicon materials [8, 32, 44], enhancing a body of liquid with rich touch sensing has mostly remained out of reach, and is a good example of *Touché*'s application range.

By interacting with water, we do not mean using touch screens under water, but *touching the water itself*. In particular, our approach can distinguish between a user *touching* the water's surface and *dipping* their finger into it (Figure 10), which is difficult to accomplish with current capacitive touch sensing techniques [7]. Resistive e.g., [31] touchpads *would* work under water, but require users to physically press on the surface, which is not truly interaction with the liquid, but rather with a submerged touchpad. Mechanical [41] or optical [26] techniques introduce large external sensing apparatus, prohibiting ad-hoc and mobile interactions. Furthermore, optical sensing generally requires controlled lighting and clear liquids. Water-activated electrical switches [45] can be used to detect the presence of water, but not the *user* playing with water. These are just a few of the challenges of user-liquid interaction.

Touché can easily add touch sensitivity to various amounts of liquid held in any container (Figures 5c). Simply by placing the electrode on the bottom of the water vessel, we can detect a user touching the surface, dipping their fingers in the water, and so on (Figures 10). The container can be made of any material, and the electrode can be affixed to the outside – although putting it inside increases sensitivity.

Applications of water sensing are mostly experiential, such as games, art and theme park installations and interactive aquariums. We can also track indirect interactions, i.e., when users are touching water via a conductive object. In this way children's water toys and eating utensils could be easily enhanced with sounds and lights (Figure 1c).

TOUCHÉ EVALUATION

In the previous section we described five example application domains where *Touché* could enhance touch interaction. For our evaluation, we selected an exemplary configuration and gesture set from each of these five domains designed specifically to tax our system's accuracy. Not only does this minimize the potential for accuracy ceiling effects, but also enables us to estimate the "sweet spot" in gesture set size and composition through several post-hoc analyses that are discussed subsequently.

These studies serve several purposes: 1) to demonstrate the wide variety of applications and interactions enabled by *Touché*, 2) to underscore the immediate feasibility of *Touché*, 3) to explore the potential richness of gesture vocabularies our system could support, and 4) to establish the baseline performance of the recognition engine.

Participants

We used two groups of 12 participants. The first group completed the first four studies (9 males, 3 females, mean age 27.6). A second group of 12 completed the final liquid study created at a later date (10 males, 2 females, mean age 28.6). Each study was run independently allowing us to distribute data collection over approximately a seven-day period. This permitted us to capture natural, real-world variations in e.g., humidity, temperature, user hydration and varying skin resistance. Although we do not specifically control for these factors, we show that our system is robust despite their potential presence. In fact, our "walk-up" general classifiers were specifically designed to model these temporal and inter-participant variances.

Procedure

The five studies followed the same basic structure described below. Each study was run independently; the entire experiment took approximately 60 minutes to complete.

Training

Participants were shown pictographically a small set of gestures and asked to perform each sequentially. While performing gestures, the participants were told to adjust their gestures slightly, e.g., tighten their grip. This helped to capture additional variety that would be acquired naturally with extended use, but impossible in a 60-minute experiment.

While the participants performed each gesture, the experimenter recorded 10 gesture instances by hitting the spacebar and then advanced the participant to the next gesture until all gestures were performed. This procedure was repeated three times providing 30 instances per gesture per user. In addition to providing three periods of training data useful in post-hoc analysis, this procedure allowed us to capture variability in participant gesture performance, obtaining more gesture variety and improving classification.

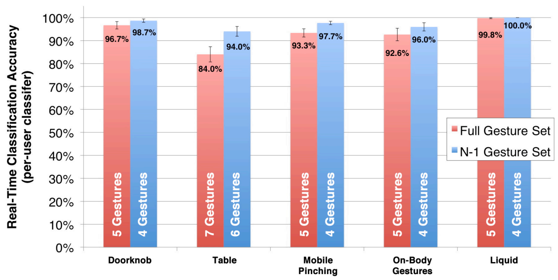


Figure 11. Real-time, per-user classification accuracy for five example applications.

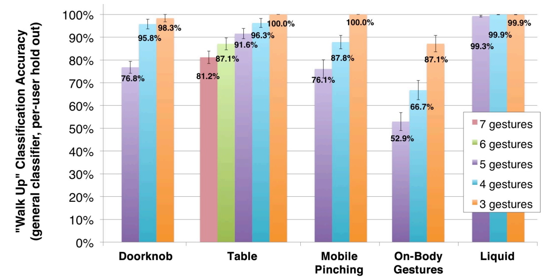


Figure 12. "Walk Up" classification accuracy for five example applications.

Testing

Following the training phase, collected data were used to initialize the system for a real-time classification evaluation. Participants were requested to perform one of the gestures from the training set randomly selected and presented on a display monitor. The system – invisible to both the experimenter and participants – made a classification when participants performed each gesture. A true positive result was obtained when the requested gesture matched the classifier's guess. The experimenter used the spacebar to advance to the next trial, with five trials for each gesture.

Accuracy Measures

Our procedure follows a per-user classifier paradigm where each participant had a custom classifier trained using only his or her training data. This produces robust classification since it captures the peculiarities of the user. Per-user classifiers are often ideal for personal objects used by a single user, as would be the case with, e.g., a mobile phone, desktop computer, or car steering wheel.

To assess performance dimensions that were not available in a real-time accuracy assessment, we ran two additional experiments post-hoc. Our first post-hoc analysis simulated the live classification experiment with *one fewer* gestures per set. The removed gesture was the one found to have the lowest accuracy in the full gesture set. For example, in the case of the grasp-sensing doorknob study, the *circle* gesture was removed, leaving *no touch*, *one finger*, *pinch* and *grasp* (Figure 6) Accuracy typically improves as the gesture set contracts. In general, we sought to identify gesture sets that exceeded the 95% accuracy threshold.

Our second post-hoc analysis estimated performance with "walk up" users – that is, classification without any training data from that user, a *general classifier*. To assess this, we trained our classifier using data from eleven participants, and tested using data from a twelfth participant (all combinations, i.e., 12-fold cross validation). This was the most challenging evaluation because of the natural variability of how people perform gestures, anatomical differences, as well as variability in clothes and shoes worn by the participants. However, this accuracy measure provides the best insight into potential real-world performance when per-user training is not feasible, e.g., a museum exhibit or theme park attraction. Moreover, it serves as an ideal contrast to our per-user classifier experimental results.

EVALUATION RESULTS

Figures 6 though 10 illustrate the physical setup and accompanying touch gesture sets for each of the five application domains we tested. Real-time accuracy results for all five studies are summarized in Figure 11. "Walk -up" accuracies with different-sized gesture sets are shown in Figure 12.

Study 1: Making Objects Touch and Grasp Sensitive

A doorknob was an obvious and interesting choice for our touch and grasp sensing study setup (Figure 6). We used a brass fixture that came with a high-gloss coating, providing a beneficial layer of insulation. A single wire was soldered to the interior metallic part of the knob, and connected to our sensor. As doors are fixed infrastructure, we grounded our sensor in this configuration. This is a minimally invasive configuration that allows for existing doors to be easily retrofitted with additional touch sensitivity.

A set of five gestures was evaluated as seen in Figure 6: *no touch*, *one finger*, *pinch*, *circle*, and *grasp*. This setup performed well in the real-time per–user classifier experiment, at 96.7% accuracy (SD=5.6%). Dropping the *circle* gesture increased accuracy to 98.6% (SD=2.5%).

Walk-up accuracy was significantly worse for five gestures – 76.8% (SD=9.2%), where the *circle* gesture was responsible for 95.0% of the errors. Once the *circle* gesture was removed, walk-up accuracy improves to 95.8% (SD=7.4%).

Study 2: Body Configuration Sensing

To evaluate performance of *Touché* in body posture recognition scenarios, we constructed a sensing table. This consisted of a conventional table with a thin copper plate on top of it, covered with a 1.6 mm glass fiber and resin composite board (CEM-1) (Figure 7). A single wire connected copper plate to the *Touché* sensor board. The static nature of a table meant that we could ground the sensor to the environment in this configuration.

A set of seven gestures was evaluated: *not present*, *present*, *one hand*, *two hands*, *one elbow*, *two elbows*, *arms* (Figure 7). Average real-time classification performance with seven gestures was 92.6% (SD=9.4%). Eliminating the *two elbows* gesture boosted accuracy to 96.0% (SD=6.1%).

Walk-up accuracy at seven gestures stands at 81.2%. As seen in Figure 12, accuracy surpasses 90% with five gestures (*not present*, *present*, *one hand*, *two hands*, *two elbow;* 91.6%, SD=7.8%). With only three gestures (*presence*, *two hands*, *two elbow*), accuracy is 100% for every participant.

Study 3: Enhancing Touchscreen Interaction

The application possibilities of *Touché* to touchscreen interaction are significant and diverse. For both experimental and prototyping purposes we chose mobile device form factor (Figure 8). Mobility implies the inability to ground the sensor, making this setup particularly difficult.

As a proof of concept, we created a pinch-centric gesture set which could be used for, e.g., a "right click", zoom in/out, copy/paste, or similar function [23]. Our mobile device mockup has two electrodes: the front touch surface, simulating a touch panel, and the backside of the device. A *Touché* sensor is configured to measure the impedance between these two surfaces through the participant's hand connecting them (Figure 5d).

Figure 9 depicts a set of five gestures that were evaluated: *no touch*, *thumb*, *one finger pinch*, *two finger pinch* and *all finger pinch*. Per-user classifier accuracy with all gestures is 93.3% (SD=6.2%). Removing the *two finger pinch* brings accuracy up to 97.7% (SD=2.6%). Walk-up accuracy at five gestures is 76.1% (SD=13.8%), too low for practical use. However, by reducing the gesture set to *no touch*, *thumb* and *one finger pinch*, accuracy is 100% for all participants, showing the immediate feasibility for mobile applications.

Study 4: On-Body Gesture Sensing

Unlike the previous three studies, human-gesture sensing has a predefined device – the human body. This leaves us with two design variables: sensor placement and gestures. For this study, we chose to place an electrode on each wrist, worn like a watch. The *Touché* sensor measured impedance between wrist electrodes through the body of participants. Due to the highly variable and uncontrolled nature of the human body, this experimental condition was the most challenging of our five studies.

Our gesture set consisted of five gestures: *no touch*, *one finger*, *five fingers*, *grasp*, and *cover ears* (Figure 9). Real-time, per-user classification accuracy was 84.0% (SD = 11.4%) with five gestures. Removing a single gesture – *one finger* – improved accuracy to a useable 94.0% (SD=7.4%). In contrast, walk- up accuracy with a general classifier does significantly worse, with all five gestures yielding 52.9% accuracy (SD=13.8%). Reducing the gesture set to three (*no touch*, *five fingers*, *grasp*) only draws accuracy up to 87.1% (SD=12.5%) – stronger, but still too low for robust use.

This divergence in accuracy performance between per-user and general classifiers is important. The results suggest that for on-body gestures where the user is both the "device" and input, per-user training is most appropriate. This should not be particularly surprising – unlike doorknobs, the individual differences between participants are very significant, not only in gesture performance, but also in their bodies' composition. A per-user classifier captures and accounts for these per-user differences, making it robust.

Study 5: Touching Liquids

We attached a single electrode under a 250 mm-wide and 500 mm-long fish tank, and filled it to a depth of 35 mm of water. The electrode was separated from the liquid by a pane of 3 mm-thick glass and attached to the *Touché* sensor board via a single wire (Figures 5c).

Our test liquid gesture set consisted of *no touch*, *one finger tip*, *three finger tips*, *one finger bottom*, and *hand submerged* (Figure 10). This experimental condition performed the best of the five. Real-time, per-user classification accuracy with the full gesture set was 99.8% (SD=0.8%). "Walk-up" classification performance was equally strong with all five gestures: 99.3% (SD=1.4%). Removing *three finger tips* improves accuracy up to 99.9% (Figure 12).

Anatomical Factors

Touché is sensitive to variations in users' anatomy. To test if anatomical variations have a systematic effect on classification accuracy, we ran several post hoc tests. We found no correlation between accuracy and height (1.6 ~ 1.9m), weight (52 ~ 111kg), BMI (19.6 ~ 32.3), or gender. This suggests the sensing is robust across a range of users.

DISCUSSIONS AND CONCLUSION

Touché has demonstrated that multi-frequency capacitive sensing is valuable and opens new and exciting opportunities in HCI. Would it be possible to achieve the same results with fewer sampling points? What are the optimal sweeping ranges and resolutions needed to achieve maximum performance and utility of such a sensing technique?

Optimizing and fine-tuning SFCS for specific configurations and uses is a subject of future work and, therefore, beyond the scope of the current paper. In general, however, designing any SFCS solutions can be considered as a sampling problem, i.e., how many samples and what frequency bands would allow us to accurately identify the state of the system? In the current implementation of *Touché* we used 200 samples between 1 KHz and 3.5 MHz. Empirically, we found it to be a good trade-off between speed and accuracy of the recognition. More importantly, it allowed us to capture details of shapes of capacitive profiles, which was important in some of the *Touché* applications, e.g., in hand-to-hand gestures. Therefore, decreasing the sweep resolution would improve performance, but also reduces the robustness of gesture recognition in some of applications.

We found that it was difficult, if not impossible, to determine a-priori which frequency bands are most characteristic for specific interactions, applications, users, materials and contexts. Indeed, around 1 MHz looks useful on Figure 9, but not at all on Figure 10. Therefore, we designed the most general sensing solution by sampling over a broad range of frequencies. Consequently, *Touché* – without any modification – enables a rich swath of interactions from humans, to doorknobs, to water. This would be impossible if we limited the range of frequencies. However, in practical applications the sensing can be limited to a range of frequencies that are most appropriate for a particular product, reducing cost and improving robustness.

Our work on *Touché* was broadly motivated by the vision of disappearing computers postulated by Mark Weiser [43]. He argued that computer must disappear in everyday objects and "… *the most profound technologies are those that disappear*". As powerful and inspiring as this vision is, it imposes a significant problem: how we will interact with computers that are invisible? From the end-user perspective, the interface will appear as a computer as long as there are buttons to press and mice to move, and thus will never truly disappear. Completely new interaction technologies are required, and we hope that this work contributes to the emergence of future ubiquitous computing environments.

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