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Sensing Opportunities for Personalized Feedback Technology to Reduce Consumption

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ABSTRACT
Most people are unaware of how their daily activities affect the environment. Previous studies have shown that feedback technology is one of the most effective strategies in reducing electricity usage in the home. In this position paper, we expand the notion of feedback systems to a broad range of human behaviors that have an impact on the environment. In particular, we enumerate five areas of consumption: electricity, water, personal transportation, product purchases, and garbage disposal. For each, we outline their effect on the environment and review and propose methods for automatically sensing them to enable new types of feedback systems.

Author Keywords
Sensing, Feedback Technology, Sustainability, UbiComp

ACM Classification Keywords
H5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

INTRODUCTION
Everyday human behaviors (e.g., home energy use and personal travel) are directly responsible for 28% of US energy consumption and 41% of US CO_2 emissions (Shui and Dowlatabadi, 2005). Most people, however, are unaware of how their daily activities affect the environment nor how often they engage in those activities. Feedback has been shown to be one of the most effective strategies in reducing electricity usage in the home (Geller, 1982). Because of limitations in sensing, however, there has been a dearth of feedback technologies in other domains, such as personal transportation and water usage. With the advent of low-cost sensing technologies, fast computation, and advances in machine learning, we now have the potential to provide personal, relevant feedback in real time for a variety of consumption activities.

In this paper, we highlight the state-of-the-art in sensing electricity, water, personal transportation, product purchases, and garbage disposal. In particular, we focus on resource consumption that is within an individual's primary locus of control. For each of the five consumption areas, we briefly outline their impact on the environment and review methods for automatically sensing them. For some areas, like electricity, a large number of sensing approaches already exist to measure energy consumption (driven in large part by utility companies' need to charge based on utilization as well as the ease in which this data can be sensed)—for others, like transportation or product purchases, very few sensing methods exist. In some cases, we also propose our own methods or suggest ways in which existing sensing systems could be reappropriated for the purposes of feedback technology to reduce consumption.

The goal here is twofold: (1) to inform the reader about the ways in which environmentally impactful human behaviors can be sensed; (2) to inspire thinking about ways in which these new types of sensor data may be aggregated, analyzed, and fed back to the individual in order to increase awareness about environmentally impactful activities and motivate sustainable behaviors. The scope of this paper prevents us from discussing particular feedback designs or visualizations (for a review see Pierce et al., 2008 and Froehlich, 2009) and instead focuses primarily on the sensing aspects.

Some open questions worth considering while reading through the rest of the paper:

- How can we automatically sense and measure the ways in which human activities impact the environment? Is this something that even should be done?
- How do we present this information to the user? Will the effective feedback strategies used to reduce home energy consumption (Fischer, 2008) translate to other environmentally impactful activities such as transit and trash disposal habits?
- Certain activities, such as plane rides, dwarf the impact of other activities. What are the implications of such contrasts for motivating sustainable behaviors?
- Assuming environmentally impactful activities can be sensed, how can we reduce the cognitive burden of consuming all of this information, particularly given that "the environment" is rarely a first-order concern of individuals when making decisions?
- How do we reconcile the paradox of creating new sensing/feedback technologies to reduce energy consumption when the manufacturing, distribution and powering of such technologies has an environmental impact itself?

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HOME ELECTRICITY USAGE

The consumption of electricity is unlike most consumable goods: it is abstract, invisible, and untouchable (Fischer, 2008). Without a tangible manifestation, home energy usage often goes unnoticed—unlike, for example, the decreasing amount of milk in the fridge, the increasing dullness of a razor blade, or a gas gauge nearing empty. In addition, energy consumption is never a goal within itself but rather a by-product of a wide variety of diverse actions such as doing laundry, driving to work, staying warm, or watching television. The residential sector accounts for 21% of the nation's energy use contributing 20% of CO2 emissions into the air (US Department of Energy, 2006). Moreover, about two-thirds of fossil energy used to produce electricity is lost in production, transmission and distribution, which means that the electricity consumed is about three times as carbon intensive as the primary energy source used in its production (Bin and Dowlatabadi, 2005).

Traditionally, there are two types of electricity sensing systems for the home: (1) plug-in load meters that measure the power draw of electrical units plugged into them (*Kill-A-Watt*[1], *Watt's Up*[2]) and (2) transformer/transducer sensors clipped-on to the home's main circuit breaker or electric meter that provide household-wide (aggregate) energy usage information (*The Energy Detective*[3] (TED), *PowerCost Monitor*[4]). Plug-in load meters typically sense and provide feedback (e.g., via a small monochrome LCD screen) within the same unit. Aggregate sensors communicate their measured values to a feedback display via a dedicated hardwire connection, wirelessly, or through internal home power lines themselves (using a technique called power-line carrier, PLC). See Figure 1.

Literature in environmental psychology has shown that appliance-level specificity increases the effectiveness of feedback (Fischer, 2008). Sensing solutions that provide detailed, appliance specific breakdown of energy usage either require several sensing units placed strategically at outlets throughout the home (plug-in meters) or multiple sensors installed at the circuit breaker box. For example, the Whirlpool Corporation designed a breaker-box system of the latter type, which could provide per-device energy levels assuming the home's circuits were partitioned in an amenable manner. However, they found no standard circuit partitioning method across homes: "*While one home may have several bedrooms combined onto a single circuit, another home combined the sockets in two bedrooms with part of the living room*" (Horst, 2006).

[1] http://www.thinkgeek.com/gadgets/travelpower/7657/

[2] http://www.wattsupmeters.com

[3] http://www.theenergydetective.com/

[4] http://www.powercostmonitor.com/

Figure 1. (left) The Kill-A-Watt plug-in load meter. (right) The Energy Detective uses sensors that clip-on to the home's main circuit breaker.

In contrast to the above approaches, we have developed a sensor capable of detecting device specific energy use with only a single, plug-in module (Patel, 2007). Our system records and analyzes electrical noise on the power line caused by the switching of electrical loads. Machine learning techniques applied to these patterns identify when unique events occur. Examples include human-initiated events, such as turning on or off a specific light switch or plugging in a CD player, as well as automatic events, such as a compressor or fan of an HVAC system turning on or off under the control of a thermostat. By observing actuation of certain electrical devices, the location and activity of people in the space can be inferred and used to create new types of feedback displays. For example, a light turning on inside the kitchen and then the refrigerator or microwave when its door is opened might indicate meal preparation. Thus, we could feedback information to the resident not just about how much energy the microwave consumed but link it to a higher-level human activity, that of meal preparation. We believe that linking not just specific appliance use to energy consumption but the human activity around that use will provide additional, useful insights to the user about their consumption habits.

HOME WATER USAGE

Water is essential to many activities around the home including washing, cleaning, cooking, drinking and gardening. Yet, the consumption of water in residential homes is a serious concern. Homes use more than half of publicly supplied water in the US, which is significantly more than either business or industry (EPA, 2008). According to US government estimates, 36 states will face serious water shortages in the next five years (EPA, 2008). Simply a 15% reduction in water usage across US households would save an estimated 2.7 billion gallons a day and more than $2 billion per year (American Water Works Association, 2001). This does not incorporate the impact such a reduction would have on water utilities, which currently consume about 56 billion kWh per year to supply and treat the water—enough electricity to power more than five million homes for an entire year (WaterSense, 2009). In addition, water heating accounts for

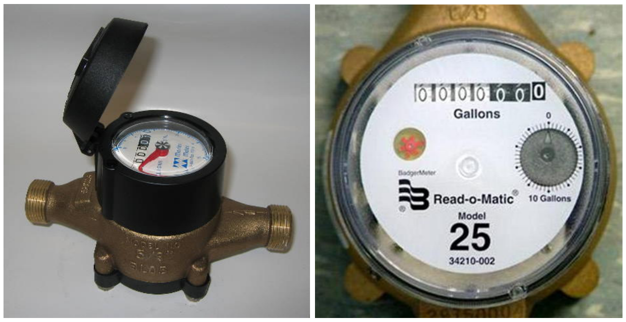

Figure 2. A typical public utility supplied water meter

9.1% of energy usage in the home (Energy Information Administration, 2001) so it is critical for residents to differentiate the amount of heated vs. non-heated water.

Most water utility companies provide home water usage meters for billing purposes, but these are often outside the home, measure water in esoteric units (cubic centimeters rather than gallons), do not provide fixture-level feedback, and do not communicate with a home network (Figure 2). There has recently been a large push towards Automatic Metering Technology (AMR) amongst utility companies, which automatically send water, gas, and/or electricity usage information to their centralized databases. This reduces the need for utility employees to physically check meters (eliminating travel and transcription errors) and also enables bills to be based on real consumption rather than on an estimate based on previous consumption. Companies such as *Greenbox Incorporated*[5] are pairing with utility companies to build personalized energy portal websites to enable households to access their real-time data feeds. AMR offers an interesting avenue to explore for easy-access to resource consumption data; however, it still uses existing measuring technology, which only provides aggregate information on consumption (and not at a fixture level).

There are two basic approaches for measuring water flow: positive displacement and velocity (Satterfield, 2009). Positive displacement systems rely on the water to physically displace the measuring element (e.g., a piston or nutating disc) in proportion to water flow volume. This approach is generally very accurate at low to moderate flow rates, which is typical in the residential sector and thus most residential meters use positive displacement. Velocity meters measure the velocity of water through a known cross-sectional area and convert this into flow volume. There are many types of velocity meters including turbine, multi-jet, magnetic, propeller and ultrasonic (see Satterfield, 2009).

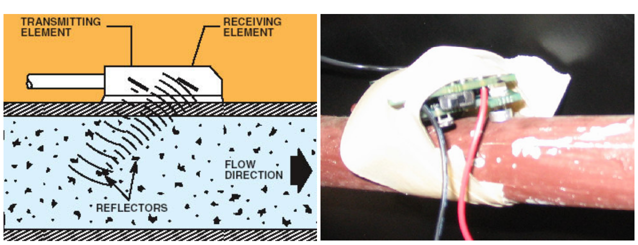

Figure 3. (left) A diagram of how ultra-sonic water meters work. (right) The audio-based water sensing system developed by Fogarty et al. (2006).

[5] http://getgreenbox.com/

Similar to electricity sensors, there are two primary locations for sensing water usage: (1) at the water fixture itself, which provides localized information about water flow at that particular fixture (Arroyo et al., 2005; Kuznetsov et al., 2009); and (2) at the primary intake pipe, which provides aggregate information on water usage for the entire household. Unlike electricity usage sensing systems, however, water usage sensing systems of any sort are not widely available for purchase in the residential sector. The main problems are the often prohibitive cost of installation, which requires access to and modification of pipes in the home, and the lack of standardization in plumbing (e.g., pipe size, intake/output pipe location, etc.).

Ultrasonic flow meters (a type of non-intrusive velocity meter) do not use mechanical pieces to measure flow and thus do not require inline pipe installation; instead, they attach to the outside of pipes and use ultrasonic waves to measure flow (left image in Figure 3). Unfortunately, however, this technique typically requires particulates or bubbles in the stream, so does not work well with distilled or drinking water. Instead, ultrasonic flow meters tend to be well-suited for industrial application and are priced for that market ($2,000 – 5,000).

We are building a non-intrusive system similar to the ultrasonic flow meters that utilizes sound and vibration to measure water usage, based on the work of Fogarty et al. (2006, see also right image in Figure 3) and Kim et al. (2008). Unlike the ultrasonic meters, we focus on the audible frequency range or, more specifically, the frequency response range supported by commodity microphones. Like our electricity sensor, we leverage the home’s existing infrastructure to sense usage. Fresh water enters a home at a single point and wastewater leaves the home at a handful of locations. We use a set of *low-cost* microphone and accelerometer-based sensors at these critical locations linked via low-powered ZigBee wireless connections. Attached to the outside of existing pipes, these sensors listen for the flow of water. Based on a model of water flow into and out of a home, we attempt to provide approximately the same information that would be obtained by installing sensors directly on sinks, toilets, showers, and appliances throughout the home. Our current work is focused on deploying these sensing units to multiple homes and trying to determine specific flow volume from the acoustic/vibration signature data.

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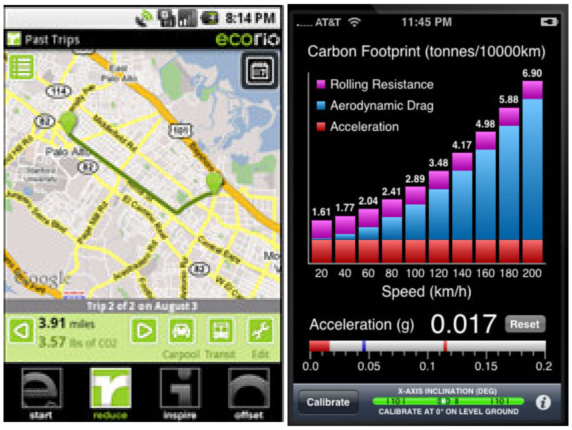

Figure 4. (left) ecorio runs in the background of the phone and keeps track of car and bus trips via GPS to calculate carbon impact. (right) greenMeter uses the mobile phone's internal accelerometer to measure forward acceleration and compute fuel economy and carbon footprints.

TRANSPORT

Home energy and personal transport are the top two contributors of the average American's CO_2 emissions into the environment (Weber and Matthews, 2007), accounting for over 50% of their total carbon footprint. Transportation alone accounts for more than two-thirds of oil consumption in the US (Davis, 2008). In 2006, highway vehicles (cars, trucks, motorcycles, and buses) were responsible for over 80% of all transportation petroleum use (including air, water, and rail). Nearly half (44%) of US carbon emissions are from oil use.

A large corpus of previous work exists on using wearable sensors to infer transportation modes such as walking, running and bicycling (Ermes et al., 2006; Lester et al., 2006; Parkka et al., 2006). Although the recognition performance is quite high, the burden of wearing and managing multiple sensors makes this approach impractical for most individuals, particularly for applications that require constant sensing. To mitigate this issue, some researchers have focused on reappropriating existing sensors available in commodity mobile phones. This has often meant leveraging the device's radio signal (e.g., GSM, WiFi) to infer motion (Sohn et al., 2006; Krumm and Horvitz, 2004). Such data is often coarse-grain, however, and does not provide enough resolution to accurately discriminate between specific transit activities.

More recently, SmartPhones such as the Apple iPhone and the T-Mobile G1 (Google's Android phone) have begun to integrate fairly sophisticated sensors such as accelerometers and GPS into the device itself. This sensor convergence has enabled a slew of research projects aimed at inferring human motion from built-in mobile phone sensors (Zheng et al., 2008; Saponas et al., 2008). For example, in a controlled laboratory study of eight participants, Saponas et al. showed how the iPhone's built-in accelerometer could be used to distinguish between walking, running, biking and standing with >95% accuracy. Zheng et al. (2008) were able to automatically infer walking, driving, bus, and bicycling using GPS with a minimum average precision of 66%. We are currently exploring how combining mobile phone accelerometer data with GPS may be used to automatically discriminate between driver and passenger. This is important for mobile applications, such as the UbiGreen Transportation Display (Froehlich et al., 2009), that reward carpooling but not driving alone. In addition, we believe that relying on the accelerometer over GPS may be more energy efficient. Other possible methods for determining if two people are riding in the same car: detecting real-time route similarity between two or more mobile GPS traces (Froehlich and Krumm, 2008), sensing co-located Bluetooth signals (Eagle and Pentland, 2005).

In light of these new SmartPhones, some commercial and open-source projects have been released that take advantage of the sensor integration. *Ecorio*[6] (left image, Figure 4) runs on Google Android phones and uses GPS to keep track of bus and car trips, which are then used to automatically calculate a personalized carbon footprint. The *greenMeter*[7] iPhone application (right image, Figure 4) uses the built-in accelerometer to compute the user's vehicle power and fuel usage characteristics to reduce fuel consumption and cost. It's unclear whether the iPhone accelerometer is accurate enough for such analysis; in addition, the greenMeter's interface is rather advanced and geared more towards car enthusiasts. *Carbon Tracker*[8], for the iPhone, calculates transportation-based carbon footprints based mainly on self-report but can use GPS to determine the length of the journey so that reported trip distances are more accurate.

Other potential sources of personal transit related information include in-car navigation systems, online travel sites like *Dopplr*[9] which tracks travel schedules (and now includes a CO_2 calculator), online bill statements from credit card purchases of gasoline, online histories of public transportation usage for systems that use digital payments systems. For example, Barcelona's Bicing system uses RFID membership cards to track shared bicycling usage (Froehlich et al., 2008) and Japan allows individuals to pay for the subway using near-field communication on their cell phones.

PRODUCT PURCHASES

For the purposes of this section, we define "product" as a good that can be purchased (e.g., in the retail setting). This may include food and drink, tobacco, furniture, cleaning products, appliances, clothing, etc. The environmental

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[6] http://www.ecorio.org

[7] http://hunter.pairsite.com/greenmeter/

[8] http://www.clearstandards.com/carbontracker.html

[9] http://www.dopplr.com

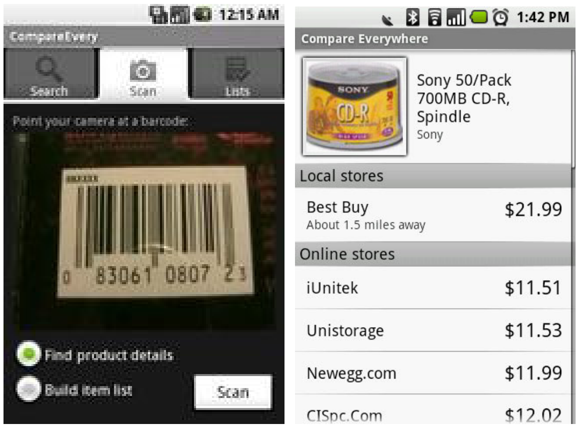

Figure 5. CompareEverywhere uses the mobile phone camera as a barcode scanner to retrieve pricing information and recommend nearby stores *in situ*.

impact of a product consists of its entire lifecycle from "cradle-to-grave," which includes production, delivery, and disposal (we focus on waste in the next section). Typically, food and drink is cited as a major contributor to environmental impacts; this includes the full food production and distribution chain from "farm-to-fork" (Tukker, 2006). Meat has the most impact within this consumption area, followed by dairy products. In a review of seven exemplar studies on the environmental impacts of products, a European Union report (Tukker, 2006) found that four concerns were typically highlighted: global warming, acidification, photochemical ozone formation, and eutrophication (a process whereby water bodies, such as lakes or streams, receive excess nutrients that stimulate excessive plant growth).

Automatically sensing of product purchases is a difficult problem, particularly *in situ*. One potential method would be an augmented reality system that constantly records what an individual sees and then feeds back information about environmental impact. Since this would require a SenseCam-like system (Hodges, 2006) paired with near perfect computer vision for object recognition it is currently technologically infeasible (not to mention the privacy implications). A somewhat less intensive approach would be something like the *Amazon Mobile Application*[10], which allows users to upload a photo of any item and provides pricing information after a five minute delay via email (if the item exists in the Amazon.com catalog). The system relies on crowd-sourcing for product recognition rather than advanced computer vision techniques. Another approach is to identify products using the built-in mobile phone camera as a barcode scanner, a technique first pioneered by Smith et al. in 2003 with AURA. *ShopSavvy*[11] and *CompareEverywhere*[12], for example, allow users to search for the best prices online and through inventories of nearby stores using a mobile phone's built-in camera and GPS (Figure 5).

These applications emphasize price comparison but could be easily modified to include details on environmental impact. In addition, their information need not be tied directly to the product itself but also to the environmental practices of the store selling the product. Indeed, the *GoodGuide iPhone Application*[13] provides an easy way to search for information on the health, environmental, and social performance of everyday products and companies (e.g., the impact of the creation of the product and/or the chemical content). In all of these examples, the user must manually search for information.

RFID (Radio Frequency Identification) tags, which can be read without a line of sight unlike bar codes, also pose new opportunities to sense products *in situ*; however, the technology is still too nascent and expensive to supplant UPC as the standard tracking label. Wal-Mart is utilizing RFID to lower operational costs by streamlining the tracking of stocks, sales and orders as RFID can be used to pinpoint individual items as they move across a global set of locations from factories, vehicles, and stores (Want, 2006). Thus, there could be a time in the future when most products (even candy bars) are imbued with RFID and mobile phones could be integrated with small RFID readers such that a quick swipe would be sufficient to identify the product. Of course, some products such as produce and restaurant foods are not amenable to RFID or UPC bar codes. So, this solution would not scale to all product purchases. Some restaurants may be open to listing environmental impact information or placing bar codes next to menu items to allow customers to track consumption and receive information about the environmental impact of their

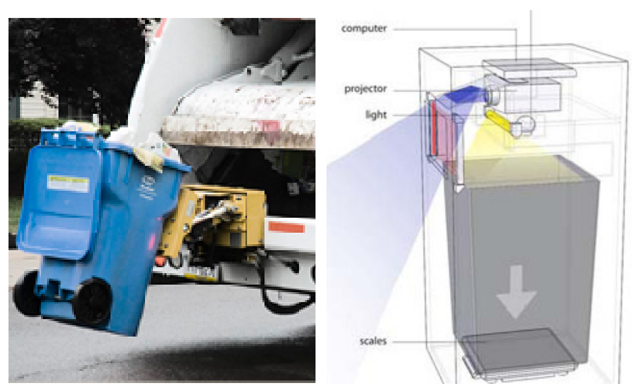

Figure 6. (left) RecycleBank automatically tracks household recycling using RFID and electronic scales. (right) JetSam is a prototype trash tracking system that snaps pictures and weighs trash as its deposited.

[10] http://www.amazon.com/gp/feature.html?ie=UTF8&docId=1000291661

[11] http://www.biggu.com/

[12] http://compare-everywhere.com/

[13] http://www.goodguide.com/about/mobile

food.

A completely separate source of product purchase information, which is not *in situ*, but could provide a basis for a comprehensive analysis of all product purchases is the combination of electronic receipts and credit card statements (Schwartz et al., 2009). Electronic receipts are common for online purchases but not so for brick-and-mortar retail. Companies like *Commerciant*[14] are beginning to offer restaurants and retailers solutions for storing and retrieving electronic receipts with customer signatures but this data is not made available to the customers themselves. Whereas credit card statements provide only information on the location, source, and cost of purchase, an electronic receipt would also include an itemized list of purchases. Accounting programs such as Microsoft Money or Quicken could provide analytic tools to measure the environmental impact of purchases, just as they do for measuring purchase behavior.

GARBAGE

The EPA reports that in 2007 the US generated approximately 254 million tons of municipal solid waste (MSW)—this is about 4.6 pounds per person per day, or roughly 130,000 pounds over an average lifetime (EPA Office of Solid Waste, 2008). The average American manages to recycle 1.5 of the 4.6 pounds per day (~33%); however, the rest ends up in landfills (54%) or combusted for energy (13%). Many of the materials typically found in household waste such as batteries, aerosols, oils, acids, and fluorescent tubes have hazardous environmental impacts. In addition, the entire lifecycle of waste, from the manufacturing and transportation of products and product packaging to the infrastructure required to deal with its disposal (e.g., garbage trucks, landfills) has an enormous ecological consequence.

How can we sense what a person throws away—particularly as they move about the world discarding items at home, work, parks, on the street, etc? This problem is far from being solved; however, constraining it to sensing the amount of trash a household or business generates is a much more tractable. Recently, waste management organizations in England have begun installing RFID tags in garbage cans. Garbage trucks then weigh the cans and scan the RFID tag to calculate the amount of trash generated by that household for the week (Null, 2006). This idea has infiltrated recycling programs as well; *RecycleBank*[15] (left image, Figure 6) uses a similar method for tracking how much a home recycles and gives back reward points that can be redeemed at retailers. If and when RFID becomes pervasive, it could also make recycling/trash centers more efficient as the products could be immediately identified for sorting.

There have also been a few attempts sensing garbage within the HCI community (Holstius et al., 2004; Paulos and Jenkins, 2005). Paulos and Jenkins built an augmented trashcan called *Jetsam* (right image, Figure 6) that used three types of sensors: a built-in camera (to record the trash), an infrared sensor to detect basic interactions such as adding or removing waste from the bin, and an electronic scale to measure the amount of trash. The items added to the trash were automatically photographed and logged along with their weight. Although Paulos and Jenkins built *Jetsam* as part of an Urban Probe (i.e., a thought provoking art installation), it is interesting to think about future trash and recycling bin designs in terms of their built-in sensing capabilities to, for example, automatically recognize trash that could be recycled or toxic waste such as batteries or oil that should be disposed of differently. The garbage could also attempt to associate trash with person by logging the nearest mobile phone identifiers (e.g., Bluetooth wireless ids) when a piece of trash is deposited. In the near future, however, such designs to the common trash/recycling bin are cost prohibitive.

CONCLUSION

In this paper, we highlighted five areas of consumption that impact the environment through everyday activities: electricity, water, transportation, product purchases, and waste. We outlined the state-of-the-art in automatically sensing each area and proposed others. Space limitations prevented us from discussing important issues that underlie a world pervaded by sensors, for example, privacy implications, energy used to power sensors, environmental costs of manufacturing and disposing of sensors. These issues are important, however, and deserve discussion. In addition, we focused primarily on how to sense rather than how to feed this information back to the user, which is most definitely an HCI problem and, we believe, a rich, open future area of research.

The main point of this paper was to: (1) inform researchers and practioners in the CHI community that soon a large amount of consumption-related data will be available—we should start thinking about interesting applications, interfaces, and feedback designs to make use of this data and (2) highlight the many different ways that exist to currently sense consumption, point out some limitations of sensing and propose a few new methods.

ACKNOWLEDGMENTS

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[14] http://www.commerciant.com/

[15] http://recyclebank.com/

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