Low-power Sensors and Smartphones  
for Tracking Water Collection in Rural Ethiopia  

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Abstract  
Access to clean and potable water is critical to health but is not always available in rural areas where residents must often venture far from home to collect water daily. This collection burden disproportionately falls on women and children; however, there is little research that quantifies the amount of time spent collecting water. This work seeks to quantify the water collection effort with the aim of understanding the economic and social impact of water policies and water source locations. The primary goal of the technical contribution is to enable researchers to gather accurate time data corresponding to individual water trips in an easy and efficient way. We have built a low-power wireless system that records motion and leverages Bluetooth-enabled smartphones to retrieve data from sensors attached to household water containers, and upload to a computer. We estimate that our sensor’s battery will last over two months under normal use. We deployed 4 sensors in an initial test in rural Ethiopia in the summer of 2011 and found that the non-technical researchers were able to set up the system and manage it easily under field conditions and that the data collected will permit the rigorous study of this important problem.

Keywords  

1. Introduction  
Improving access to safe, convenient drinking water remains a key development challenge in many parts of the world. According to the WHO and UNICEF Joint Monitoring Programme (2010) [9], approximately 884 million people worldwide, 37% of whom live in sub-Saharan Africa, still use unimproved drinking water sources like rivers or springs. Among policy-makers and researchers in the water sector, the focus has been predominantly on the health benefits of improving access to safe water, particularly in preventing diarrheal disease [8]. While collecting water from unimproved sources can take up to 6 hours in some cases, the establishment of community or household water taps can significantly reduce the time spent collecting water. (In the rest of the paper the term “time-use” refers to the time spent collecting water). A number of studies based on household surveys have found that water project beneficiaries often perceive the increased convenience and time savings as equally or more important than health benefits [4]. In [7] Cairncross and Valdmanis observe that “given the relevance of the time-saving benefit to water supply policy and the fact that the benefit is usually uppermost in the mind of the consumer, it is remarkable how few data have been collected on the amounts of time spent collecting water”.

What is the impact of providing convenient water supply on water carriers’ pattern of time-use, and what is that time used for? One difficulty in answering this question is measuring time-use accurately. A commonly used approach asks respondents directly: “how many minutes did you spend yesterday collecting water?” This suffers from recall bias, and also presumes a familiarity with thinking about time in terms of hours and minutes. In our study site in rural Ethiopia, only 53% of the population owns some type of time-keeping device (a watch, clock or mobile phone). To minimize recall bias, researchers ask subjects in industrialized countries to complete time-use diaries, recording their primary (and sometimes secondary) activities over one day or more. This has been impossible, however, for illiterate populations in poor countries.

In an earlier study, members of our team (researchers in the Evans School of Public Affairs at the University of Washington) elicited time-use before and after water supply projects were completed in three villages in rural north-central Ethiopia. Time was measured in three ways: with direct recall, through an interviewer-guided activity that allocated the total amount of time in the day to different categories, and with a self-completed pictorial diary paired with a simple timer set to beep every 30 minutes. However it is difficult to determine which of these three methods is most accurate without ground-truth validation of time-use.

As a first step to find accurate alternatives to measure time-use, a pilot study was conducted in the summer of 2010 in which Omron HJ720ITC pedometers [5] were attached to containers (similar to those shown in Figure 1) used for water collection. Since pedometers are fairly accurate in counting footfalls, the hope was...
that this would give an accurate measure of time-use. The HJ720ITC reports step-counts at a minimum granularity of 1 hour and can upload data to a computer over a USB connection. Figure 2 shows the hourly step-counts from the pedometer used by one of the participants. In the post-study interview, the participant reported that she spent 90 minutes after 11AM for collecting water on that particular day. However the pedometer recorded steps in the 11AM – 6PM time period because the water container was used for household activities after water collection.

It was difficult to determine time-use based only on the pedometer’s readings because step-counts were reported at an hour’s granularity. For instance, steps recorded when the container was used for shorter duration activities (e.g. washing hands) could not be eliminated as noise in the reported data. Step-count logs could be retrieved from pedometers over a USB connection with a computer, however due to the rough commutes to and from the villages it was difficult for researchers to carry a laptop for data collection. Finally, scaling up deployments based on these pedometers would have been difficult due to its high price ($60 USD per unit). Due to these limitations, the pedometer-based approach for measuring time-use was not pursued further.

This experience led us to develop a more accurate solution for this problem. In this paper, we present our sensor-based alternative for measuring time-use that addresses limitations identified in the pedometer trial. As done in that trial, our sensor is also attached to containers used for water collection and measures time-use by monitoring motion. It is able to identify movements that have a shorter duration thus making it possible to suppress noise in the signal stream. Our sensors are Bluetooth-enabled, which makes it possible for smartphones to retrieve data over a wireless connection. The phones in-turn upload this data to a central database where it can be easily accessed by researchers. It is worth mentioning that even though Bluetooth consumes significant power, we have added it to the sensor to lower a data collection barrier that is specific to the developing regions context. Time-use researchers spend a lot of time travelling between villages in developing countries to collect data. Carrying a laptop (or even a netbook) for collecting data from sensors, possibly over USB, is quite impractical. Using Bluetooth-enabled sensors lowers this barrier significantly because this enables mobile phones to be used for data collection. This choice is acceptable because the Bluetooth radio is only turned on when the researcher and phone is co-located and then only for long enough to exchange the relevant data.

The rest of the paper is structured as follows. We provide an overview of our system in the next section followed by a discussion on lessons learned from this trial before concluding the paper.

2. System Overview

Our system has three main components; namely: the sensing subsystem, an Android smartphone-based data retrieval and configuration management tool, and a deployment data aggregator tool to collect data from smartphones. The design and implementation of these components is discussed below.

2.1 Sensor

The motion-sensing device that we have built is attached to containers that are used for water collection. It records trips that are defined by a start-time and an end-time (4 bytes each). We used the Atmel processor-based Arduino microcontroller because it is competitive in its energy efficiency compared to other microcontrollers and is easy to program. Even though low-power accelerometers are typically used for motion tracking applications, we use small mercury tilt switches [1] because they do not require any power at all for operation. Mercury switches can be used as binary indicators of motion (1 when motion is detected, 0 otherwise), which is sufficient for our purposes. During testing we verified that two switches placed orthogonal to each other are sensitive enough to track motion for our application.

Our application requires accurate timestamps to record time-use; since the Arduino does not have an internal real-time clock (RTC), we have integrated an external RTC module on the board. An external 32KB EEPROM chip has also been added to persistently store up to 2 months of time-use data. A Bluetooth module enables communications with a Bluetooth-enabled mobile phone. Two AA Alkaline batteries provide 2700 milliamp hours of power.
of power to the system at 3 volts. These batteries were chosen for their ubiquity even in the developing world. The battery choice might change in the future (to rechargeable batteries), but for now it is straightforward to just replace the batteries at the end of each data collection. The model will likely always be one of battery replacement rather than recharging in the field as that takes too much of the data collectors’ time.

Our motion-sensing device is shown in Figure 3. Due to the prototype nature of our hardware, its current cost is on the higher end, but when produced at scale we expect the cost to be well under $20 per unit.

![Motion sensor](image)

Figure 3: Motion sensor used to record time-use. Its components are: 1) Arduino Microcontroller 2) Mercury Switches 3) Bluetooth Module 4) RTC Module 5) EEPROM Chip 6) 2 AA Batteries (not visible on the left). The ensemble is packaged in a black box (the final dimensions are 4.5” x 2.5” x 1”)

### 2.1.1 Power Management, Data Transfer and Trip Detection

Based on information from our collaborators we know that water collection trips can last up to 6 hours. To maximize the system’s battery-life we have programmed it to be in its low-power state at all times. It is woken up only by a change in state of the mercury switches.

Bluetooth has the highest power budget amongst all components, so it is always powered off to conserve energy. Researchers turn it on to configure the sensor before deploying at a household or to retrieve data (both of these operations are discussed in more detail later in the paper). The switch to control power to the Bluetooth module is hidden inside the enclosure so that household members don’t turn it on accidentally while they are using the water container. After turning on Bluetooth, researchers are required to shake the sensor so that interrupts from mercury switches wake the Arduino up.

The sensor’s main-loop is shown in Listing 1. Each iteration handles communication with a connected mobile phone or execution of the trip detection algorithm described below. The trip detection algorithm records the time and puts the system back to sleep to await the next bounce in a mercury switch.

Since water collection trips are always at least a few minutes long, we only record trips that are longer than \( \minMovementDuration \) minutes. An ongoing trip is considered complete if no movement is detected for \( \maxIdleDuration \) minutes. The algorithm begins by querying the current time \( (CTS) \) from the RTC. If it determines that a new trip has started, the pointer to the EEPROM’s next free location is incremented \( (\text{EEPROMWriteIndex}) \) so that the new trip’s timestamps can be recorded and the trip’s start timestamp \( (\text{STS}) \) is updated. Otherwise if the movement is already part of a valid trip (i.e. greater than \( \minMovementDuration \)) then both the trip’s start and end timestamps \( (\text{STS} \text{ and } \text{ETS}) \) are updated in the EEPROM. Finally the algorithm updates the trip’s end timestamp \( (\text{ETS}) \) after enough idle time and terminates by transitioning the device to its low-power mode.

![Listing 1: Sensor’s main-loop to communicate with phones over Bluetooth and record time-use data.](image)

We expect the device to be in its low-power mode (i.e. stationary) for most of the day, transitioning into active mode when motion is detected. Bluetooth will be active for at least a couple of times during each deployment of the device (initially to configure the device and then at the end to retrieve data). We estimate the device’s battery-life based on the following usage profile. The Arduino draws about 4.5 milliamps of current in active state and under 20 microamps in its low-power state. The Bluetooth module connected to the Arduino draws about 20 milliamps on average when in use. As a conservative estimate, if we assume the container to be in motion for about 6 hours per day and Bluetooth to be turned on for 10 minutes every day, we estimate a battery life of over two months. Figure 4 shows the projected battery life of the system as a function of the percentage of time spent by the system in its active state. The red marker on the graph is our conservative estimate of battery life.

![Figure 4: Battery life vs. time spent collecting water per day.](image)

Estimates are based on power consumption in active (4.5 mA), sleep (20uA) and Bluetooth-on (20+ mA) modes. Calculations assume use of Bluetooth for 10 minutes every day.
2.2 Android Application for Data Retrieval

Android smartphones play an important role in the system by acting as intermediary mobile nodes that manage the assignment of sensors to households and collect data from them. Using mobile phones as intermediaries makes time-use data collection and reporting much easier because researchers do not need to carry laptops or netbooks when they travel to their deployment sites. Assignment of a sensor to a household involves collecting some information about the household and configuring the sensor (this is discussed in the next section). The Android application uses Open Data Kit (ODK) [6], an open-source data collection toolkit, to collect the required household information. Sensor configuration is done by the application over Bluetooth. Figure 5 is a screenshot of the main Activity of the Android application that shows the top-level operations performed by the application. Figure 6 shows a screenshot of the Activity used to retrieve trip data from a sensor.

![Figure 5: Main Activity of the Android application that interacts with sensors. “Sensor Assignment Form” invokes ODK to collect information about the household. “Deploy Sensor” programs the unique ID of the household into the sensor. “Collect Data” retrieves data from the sensor. “Set Time on Sensor” updates the time of the sensor’s RTC Module.](image)

Figure 6: The Activity to retrieve trip data from the sensor. After connecting to the sensor over Bluetooth, researchers choose the “Start Data Collection” option to retrieve data from the sensor.

2.3 Deployment Data Aggregator

Information from mobile phones used in the field for sensor deployments and data collection is aggregated into a central database. This database could exist in the cloud but since reliable Internet connectivity cannot be assumed during these deployments, currently this database exists on researchers’ personal computers (typically laptops). A Python program running on the aggregator machine receives all the deployment data from mobile phones and stores it to a local SQLite database. Android phones also have SQLite, so if desired, the central database can also be pushed out to phones for use in the field. The aggregator allows researchers to import sensor-household assignments done in the field as well as time-use data collected from sensors. Data stored in the local database can be exported to comma-separated-value (CSV) files to facilitate analysis using a program like Microsoft Excel or imported into relational databases and statistical packages.

3. Time-use Data Collection

Time-use study of households using our system happens in three phases. It starts with Phase 1 in which a sensor is deployed at a household (i.e. attached to a water container in the house). At this time the sensor is considered assigned to that household for the purposes of the study. Additional information about the household collected at the time of deployment is shown in Table 1. This information is collected using ODK Collect that runs on researchers’ Android phones. The Android application also assigns a unique and anonymous ID to the household. This ID is programmed into the sensor over Bluetooth. This ensures any future data collection can be linked to the configuration data. The Bluetooth radio of the sensor is turned on by the researcher for this interaction and then turned off immediately afterwards. This procedure is performed for each household participating in the time-use study. Phase 1 is depicted in Figure 7.

![Table 1: Data collected in Phase 1 using an ODK form.](image)

In Phase 2 (Figure 8) the sensor autonomously detects and records time-use information using the trip detection algorithm described earlier. Table 2 shows the data persistently stored by each sensor. The 4-byte SensorID and 4-byte HouseID are stored in the first 8 bytes of the external EEPROM. This is followed by 4-byte timestamps for each trip that is detected by the sensor. At the end of the study-period researchers return to households to retrieve the time-use data stored on sensors. They turn on the...
Bluetooth radio of each sensor, activate it by shaking it and connect to it using their Bluetooth-enabled Android phone. The Android application retrieves the stored data from the sensor and stores it in its local database. The sensor’s batteries are replaced depending on the length of the study period. At this point the sensor can be redeployed to the same household or to a different household if needed.

<table>
<thead>
<tr>
<th>Data</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensor ID</td>
<td>Unique ID for each sensor</td>
</tr>
<tr>
<td>House ID</td>
<td>Unique (anonymous) ID for each house in the study</td>
</tr>
<tr>
<td>Start Time(s)</td>
<td>The time when a new trip starts</td>
</tr>
<tr>
<td>End Time(s)</td>
<td>The time when the trip ends</td>
</tr>
</tbody>
</table>

Table 2: Data stored on a sensor. The SensorID and HouseID are stored as the first 8 bytes of the EEPROM. Each trip is stored in chronological order as a pair of 4 byte timestamps

In Phase 3 (Figure 9) the researchers upload all the assignment and time-use data from their Android phones to a central computer. The aggregator program running on the computer merges and stores the assignment and time-use data into its SQLite database. At the end of phase 3 researchers have all the time-use in a digital format that can be easily analyzed and shared.

4. Deployment in Ethiopia

Development and testing of our time-use monitoring system was completed by the end of spring 2011. We then conducted usability trials with the researchers who later deployed the system in Ethiopia. After receiving some training from the developers about the system they were able to comfortably perform all the tasks in the three phases of time-use data collection. Overall, they found the system easy to use and set up. In the summer of 2011 they travelled to rural Ethiopia to deploy the system under field conditions and to get sensors’ usability feedback from the local population. Time-use data was collected from forty households in three villages over a period of four weeks. The villages, namely Beshikiltu, Kelecho Gerbi, and Tutekunche (Figure 10), are located in the Oromia region of Ethiopia. The water source options available to these villages include a nearby river, unprotected springs, and a household well. Unless a household has a well, villagers spend anywhere between one to six hours daily to collect water.

The researchers had four time-use sensors and two Android phones running our application. The sensors were time-shared amongst the households participating in this trial. The maxIdleDuration and minMovementDuration parameters used in the trip detection algorithm (discussed above) were set to 2 minutes in all the sensors. Data collection from each household happened over three days. On Day 1, the researchers deployed sensors at households and collected household information using ODK Collect (Phase 1). Each household typically has a few containers for collecting water, however only one container per household was used for data collection in this trial. Figure 11 shows one of the researchers attaching the sensor to a container. As evident from the picture, the sensor mounting and waterproofing mechanism was not very sophisticated, but it was effective nevertheless. On Day 2, a household member used the container to collect water from one of the sources. On day 3, researchers returned to retrieve the sensor and its data before reassigning it to another household. Sensor data collected on the Android phones was uploaded to the researchers’ shared laptop (Phase 3) when they returned to their base at the end of the day. Researchers also conducted a post-study interview with the person who collected water the previous day. This was done to determine if the sensor caused any inconvenience to the water collector and also to get ground truth validation data. Since water collectors do not wear watches, the time of day was reported as one of the following: morning, midday, afternoon or night. The reported duration was their best estimate of the length of the trip. The post-study questionnaire is listed in Table 3. Two other methods were
used to obtain data for ground truth validation in this study. Water collectors were asked to maintain pictorial diaries to record their daily activities during the study-period. In addition to this, the researchers also obtained GPS data for households and water sources. Analysis of the sensor data from this trial reveals that the recorded water collection trips were less than 2 hours long. 23% of the water collection trips were more than an hour long. We defer a detailed comparison of data collected from our sensor-based system and the ground truth data obtained from the three methods mentioned above to future work. However, in the remainder of this section we present some preliminary results obtained by using our system and compare it to self-reported data.

Table 3: Post-study questions

<table>
<thead>
<tr>
<th>Questions</th>
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</table>
| 1. What time of day did you collect water yesterday for this trip?  
  (Morning, Midday, Afternoon, Night)                                      |
| 2. Approximately how long was the trip to the water source?               |
| 3. Approximately how long did you wait at the source?                     |
| 4. Approximately how long was your trip back to your home?                |
| 5. Did the sensor make it difficult to carry the jerry can?                |
| 6. Did having the sensor make you uncomfortable?                          |
| 7. Did anyone notice the sensor?                                          |

Figure 11: Researcher attaching sensor to a water container. The lady is the primary water collector for the household.

Questions

Figure 12 and 13 show trips recorded by one of the sensors deployed at a household. Time periods when the sensor is moving are plotted with a value of 1 while time periods when the sensor is stationary have a value of 0. So the trips detected by the sensor are represented as pulses where the width of the pulse is the length of the trip. Figure 12 shows all the trips that were detected over the 3-day deployment period. Since $\text{minMovementDuration}$ was set to 2 minutes, the sensor recorded some short duration trips as well. For instance, consider the first couple of pulses in the graph that occurred on 7/18/11 and lasted for 12 minutes and 2 minutes respectively. These do not represent water collection trips, but are in fact the times when the water container was being used in the house, most likely for activities like cooking or washing. For time-use measurements such pulses represent noise in the data reported by the sensor and can be eliminated easily based on the width of the pulse. This figure actually has only two pulses that are long enough to be considered actual water collection trips. These occur back-to-back (a likely candidate for a long roundtrip with a short, stationary period in between to fill the container) on 7/19/11: $t=11:42$ to $t=12:51$ and $t=12:58$ to $t=14:30$ and are highlighted by a red marker in the graph. During the post-study interview the water collector said that they collected water at midday and each leg of the trip took 60 minutes. This self-reported data correlates very well with the data reported by the sensor. There is of course a discrepancy of 30 minutes in the duration of the return trip, which is likely due to the fact that self-reported durations are estimates. But it’s also quite likely that the return trip was actually longer because the collector walked back slower due to the weight of the container that was filled with water. Figure 13 is a close-up view of the water collection roundtrip reported by the sensor.

Figure 12: Trips recorded by a sensor over a 3-day deployment at a household. Trips detected by our sensor are represented as a pulse with the width indicative of the length of the trip. Single vertical lines in the graph are actually trips of very short duration (household activities in which the container was being used). The 2 pulses with a red marker indicate a water collection roundtrip.

Figure 13: A zoomed-in view of the water collection roundtrip as recorded by the sensor. The length of each trip and time of day correlate well with the water collector’s self-reported data.

Figure 14 shows trips recorded by a sensor at another household over the three day study-period. In this case the water collection trips were less than 2 hours long. 23% of the water collection trips were more than an hour long.
Figure 14: Trips recorded by a sensor over a 3-day deployment at a household. In this case 1 pulse with the red marker indicates the water collection roundtrip. The shorter duration pulses (vertical lines) indicate the water container being moved around, possibly for household activities.

In addition to getting data for ground truth validation, the post-study interview also tried to gauge the acceptability of the sensor for time-use studies (questions 5 - 8). Of the 40 participants, two used a clay-pot while the others used a jerry can as the water container. The two (5%) participants with clay-pots found it difficult to carry the container due to the attached sensor while the others did not have any problems. Six (15%) participants were hesitant while carrying their container, fearing that the sensor might break or get detached. Interestingly, 30 (75%) participants reported that passersby asked them about the sensor and what it was being used for. Two participants reported that they had hidden the sensor so that it would not be noticed. Several participants voluntarily expressed a preference for using this new method of data collection over self-reporting via interviews or pictorial diaries. They said that the new method is better for them because it doesn’t require any extra time or recall on their part. Researchers were not able to get sensor data from some of the deployments. They reported that the most likely cause for this was that the sensor had stopped working due to either a loose wire connection or dead batteries. Due to limited feedback from the sensor they realized the anomaly in Phase 2 when they were retrieving data and were unable to connect to the sensor. Despite these failures, they liked the fact that it was very easy for them to get CSV files from raw sensor data. Moreover, they said that they are easily able to identify noise in the reported data by looking at its graph. The Phase 1 sensor deployment at a household typically took 15 minutes; this includes the time needed to attach a sensor to a jerry can. Phase 2 was completed within 5 minutes at each household; this does not include the time needed for the post-study interview. Phase 3 took under a minute to upload data to a computer.

5. Discussion

The deployment in Ethiopia was the first trial of our system with an end-user community, so we did expect to uncover new issues. Nevertheless, the researchers found our system to be useful as it simplified their data collection cycle and got them to the data analysis phase sooner. Although the usability assessment done in Ethiopia was not extensive, the positive response received from study participants and researchers is extremely encouraging, which indicates that attaching sensors to containers would generally be acceptable to end-users. However, based on lessons learned from this deployment, we do need to make some enhancements to the system before doing a larger-scale deployment. Better feedback mechanisms are needed on the sensor and the Android application to help with quicker diagnosis and rectification of failures similar to those seen in the Ethiopia trial. Packaging of the sensor can be improved to reduce its size and make it more waterproof. This will also improve usability on containers like clay-pots that are fragile and have curved surfaces.

While the system presented here is a solution to a specific data collection problem, it can be generalized to enable data collection in other studies as well. Understanding how people in rural areas spend time more generally is interesting and important to researchers in the Anthropology, Development Economics, Public Health and Social Sciences communities. We believe that appropriate and simple-to-use sensors that provide fine-grained data would be complementary to their existing methods of data collection, which include in-person observations, interviews and standardized surveys.

Our algorithm for detecting time-use trips can be enhanced to monitor other everyday activities like cooking, washing etc. that involve water containers. Exploring possibilities to correlate these activities with general health outcomes of households would be valuable. Motion sensors attached to farming equipment could be used to study time spent in farming activities. Sensors, deployed for days or weeks, and occasionally coupled to smart phones to transfer data could also be used for water quality monitoring or in the agricultural domain for soil or crop monitoring.

6. Related Work

Architecturally our system is a three-tier Data MULE (Mobile Ubiquitous LAN Extension, [3]) in which mobile nodes (i.e., smartphones) collect data from sensor nodes and relay it to the central database. The difference being that in addition to collecting data from sensor nodes, mobile nodes in our system deploy and configure them as well.

Rather than discussing specific works we refer the reader to [2] that presents a survey of Wireless Sensor Networks in which Mobile Elements (ME) perform data collection. The survey
highlights challenges in the discovery phase that are unique to such systems. This is the first step in data collection and enables sensors to discover MEs in the vicinity. Several protocols have been proposed to perform discovery in an energy-efficient manner, often using secondary, lower power radios. The secondary radio periodically searches for MEs in the vicinity and turns on the primary high-power and high-bandwidth radio for data transfer only when an ME is discovered. In the current implementation we do not use a secondary, low-power radio in order to maximize the battery-life of our sensor. In our system researchers explicitly turn on the sensor’s Bluetooth radio and shake it to activate the processor prior to data collection.

7. Conclusions and Future Work

In this paper we have presented a system to monitor and report the time spent by people to collect water (time-use) in rural areas of developing countries. This information can help guide policies that govern how and where convenient water sources should be created in order to increase the positive health-impact on communities. Currently used methods can lead to discrepancies as they rely on self-reporting, which introduces recall bias; this gets amplified because water collectors have a different notion/measure of the passage of time. Our system improves the accuracy of time-use measurement and reporting by attaching low-cost, low-power sensors to containers used for water collection. Bluetooth-enabled Android phones are used to configure, deploy sensors at households and then to retrieve the data recorded on these sensors. This data is then uploaded to a central database on a computer where it can be analyzed or shared further. The system has addressed limitations identified in an earlier study that used pedometers to measure time-use.

We deployed our system in forty households of three villages in the Oromia region of Ethiopia in the summer of 2011. We have received positive feedback about the efficacy of the system from field researchers. Household members who carried containers with sensors attached to them have given positive feedback about the usability of the system. The deployment has also helped identify areas of improvement in the system that will be addressed in the near future. In 2012, we expect to return to Ethiopia with more compact sensors and do a larger scale deployment that will cover up to 500 households and will run over a longer period of time. We will explore the possibility of using an NFC tag as a switch to control the sensor’s Bluetooth module to make data collection easier in this deployment.

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References

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