Sound recording to characterize outdoor tap water use events

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ABSTRACT

Obtaining disaggregated water use at the home typically involves expensive smart metering. In this study, water use events at the outdoor tap were captured using recorded sound. Outdoor taps at 10 homes were fitted with small-sized microphones and digital sound recorders. Sound files recorded over a 1-month period were used in the analysis. In the preliminary analysis, a human operator browsed through the sound recordings, picking out tap use events based on visually recognizable waveform and spectrogram features, then audibly verified each event identified before labeling. The performance of the corresponding automatic detection algorithm was reasonable, showing that water use events can be detected at precision and recall rates of at least 80% under suitable conditions. The results also showed that the technique is less suitable where the drop in pressure during peak demand periods results in significant reduction in the tap flowrate. Indirect flow sensing approaches are attractive for investigating water use event timing, because of the relatively lower cost when compared to conventional or smart water meters. Plumbing changes are not required as the recorder can be mounted on any exposed pipe section near the fixture of interest.

Key words | outdoor tap, sound, water use

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INTRODUCTION

Assessing climate-related impacts on residential water use hinges to a large extent on the correct determination of outdoor water usage. Residential water end-use studies have further shown that disaggregated water use data unveils patterns of fixture usage that are hardly noticeable in aggregated water consumption records. Detailed knowledge of the usage of specific types of fixtures in the home improves the planning and evaluation of the relevant water conservation measures (DeOreo *et al.* 1996). A typical approach to obtain disaggregated water use data involves smart metering and flow trace analysis. The costs associated with smart metering are relatively high, so that the related studies have largely been confined to developed regions. Survey techniques such as questionnaires or diaries are cheaper but the accuracy of the results is often limited.

A number of studies have proposed indirect approaches for sensing water usage in the home at the fixture level. Human activity recognition, mediated by the home plumbing system, has been the main interest in most of the reported research. Chen *et al.* (2005), for example, examined the use of microphones to monitor the activities of patients in the bathroom. In similar work, Forgarty *et al.* (2006) mounted a microphone on the main supply pipe to sense flow every time water was used in the study home. The profile of fixture usage was then obtained by applying a pattern recognition computer algorithm. Other reported applications of microphone based flow sensing include oil and gas monitoring by Lapinski *et al.* (2007) and the monitoring of field sprayers by Zhang (2014); Froehlich *et al.* (2009) instead logged fixture use by a pressure sensor connected to the home plumbing system through any accessible valve. Kim *et al.* (2012) later tested the use of accelerometers, installed on pipework leading to water use fixtures in the home, to infer in real-time the fixture in use and estimate

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the flowrate from the measured pipe vibrations. Indirect flow sensing approaches are attractive because of the relatively lower total installation cost. Unlike inline mechanical flowmeters, accelerometers or microphone sensors do not require plumbing changes since they can be easily mounted on any exposed pipe section of the fixture of interest. Unfortunately, event volume cannot be reported as accurately as with smart metering technology.

The aim of the field study reported in this paper was to test the suitability of sound recording for capturing residential outdoor tap use events. The paper presents the microphone and sound recorder setup, the steps taken to abstract water use events from the sound recordings, and the results from the application of an automatic detection algorithm. The use of microphones was preferable to accelerometers because the recorded tap flow sound could be audibly verified during analysis. Precautions had to be taken, though, to avoid capturing sounds that would lead to privacy intrusion. The findings in this study demonstrate the potential for using recorded sound as a low-cost option for obtaining frequencies and durations of disaggregated water use events at the outdoor tap.

RESEARCH METHODOLOGY

Recorder choice and setup

Sound was captured at the outdoor tap using Sony ICD-PX333 recorders. The Sony ICD-PX333 model was chosen following a review of a number of digital sound recorders available at the time of the study. The selected sound recorder model had the capability to record continuously by automatically creating new files when the current recording reached the file size limit. The internal 4-gigabyte memory lasted approximately 6 weeks when recording at 8 kilobytes per second (kbps) in MPEG layer 3 (MP3) format. The 8 kbps recording setting was chosen because of the significant saving on computer storage space despite being the lowest recording quality for the ICD-PX333 model. The recorders were connected to an external pack of two D-type alkaline batteries instead of the usual AAA batteries in order to extend the battery life to match the total recording time of the ICD-PX333 recorder.

Study period and selection of study homes

The study was first conducted from December 2014 to January 2015 and later repeated from May 2015 to July 2015. The first study period captured the last few weeks of summer and extended into the rainy season while the second period fell in the cool dry season. Study homes were located in three neighbourhoods in the City of Lilongwe, Malawi. In the first period of the study, 10 students from the Lilongwe University of Agriculture and Natural Resources (LUANAR) agreed to have the sound recorders installed at their homes. Most shortcomings in the recorder installation and setup procedure were discovered and addressed during the first study period.

Only three homes were carried over from the first to the second study period. The other seven homes were dropped either due to limited outdoor water use or not having replanted their backyard garden with new crops at the time the study was repeated. The seven homes were replaced by selecting additional homes from a larger sample of homes that had participated in an outdoor water use survey that was carried out at about the same time as the first study period. Discussions with a handful of homeowners from the survey participants led to the identification of those who had no objection to the continuous recording of sound at their outdoor tap. The final selection was based on the availability of a home garden that was irrigated exclusively from the outdoor tap. In addition, homes where the outdoor tap was located immediately next to the main house or another building were avoided to minimize interference of sound from other water use fixtures. Hosepipes were used for garden irrigation at seven of these homes while buckets were used at the other three. The analyses presented in this paper were performed on 1-month long data from the second study period when there was more outdoor water use and the recordings were more consistent.

Installation of microphones and recorders

The outdoor taps were fitted with electret condenser microphones midway between the tap branch pipe. The microphones were covered by PVC rubber and firmly attached to the tap branch pipe using cable ties. The purpose of the rubber coverings was to protect the microphone from getting soaked with water and to block airborne sound that would complicate analysis. In order to block water vapour, the recorders were sealed in plastic pockets with tape. The sound recorders, including an external battery pack, were then covered inside tight fitting plastic enclosures that were securely placed in a hole drilled next to the tap. Holes were made through one side of the enclosures to provide a passage for microphone wires and sealed in place with water-resistant adhesive. Gardena flowmeters were screwed onto the taps to measure the total volume of water. The Gardena flowmeters stored the total volume of water used electronically and were read once every month. The volumetric flow measurements were, however, not used in the analyses because the flowmeters were tampered with at some of the homes. Figure 1 shows the complete microphone and recorder setup.

Recordings for exploring the characteristics of sound from the taps

In order to get acquainted with characteristics of the flow induced sound, six water use events were recorded at each tap at the beginning of the study. First the tap was opened fully to reach the highest possible flowrate while filling a bucket of known volume. If a hosepipe was used for garden irrigation at the respective home it was connected to the tap, otherwise the water was run directly into a bucket. Secondly, the tap was opened just enough to reach smooth flow and lastly the tap was run at an arbitrary intermediate flowrate. The procedure was repeated and the start and finish times of the events were noted. The first recordings provided insight into the expected properties of the subsequent audio signals.

Recording and preparation of recorded sound files for analysis

Files were transferred from the recorders to a computer once every month. The MP3 files were first split into 24-hour segments each of which had a size of 84 megabytes, except the last file which was shorter. The 24-hour segment length was chosen because it simplified the matching of dates and their recordings while at the same time not being too large to load into computer memory for analysis. The audio files were uncompressed to WAVE format which can be read by most computer programs as ordinary binary files. The MP3 files were converted to 16-bit wave file at a sampling rate of 11,025 samples per second. The file conversion increased the file size to 1.86 gigabytes, approximately 22 times larger than the size of the original MP3 file.

Manual extraction of tap use events

The 1-month long recordings from the second study period were manually analyzed by a human operator using

Figure 1 | Complete setup of recorder (in PVC casing) and microphone (covered by a block of PVC rubber) at the outdoor tap.

Audacity software in order to abstract water use events. In order to visualize the sound properties at each point in time, duplicate audio tracks were added to a single timeline for each file being analyzed. The first track was displayed as a waveform, while the second track was changed to display as a spectrogram of 1,024 samples per window. An additional 'label' track was added to the timeline for marking and annotating water use events identified in the recording. Tap water use events were identified from changes in the amplitude of the waveform and visually distinguishable patterns in the spectrogram. For consistency, the audio tracks were scaled to fit a 2-minute long window in the available horizontal display area of the Audacity software user interface. The appropriate keys on the computer keyboard ('Page-Up' and 'Page-Down') were pressed to scroll the tracks forward or backwards at 2-minute long intervals. Sounds lasting no more than 2 seconds were clearly recognizable. Any changes noted in the waveform or spectrogram were further examined by playing and listening to the respective segment. Sounds from other sources were separated from the typical hissing or splashing sound associated with a running tap. Only tap flow events lasting for at least 2 seconds were labelled. Once a file had been browsed through to the end, all labels created for each file were copied to an Excel workbook for further analysis. A single 24-hour file took about 15–30 minutes to analyze depending on the number of sound events present.

Audio features used for automatic change-point analysis

Manual abstraction of water use events from the sound files proved to be a laborious and time-consuming procedure. A more realistic approach is to use computational techniques to automate the detection of water use events from the sound files. An automatic algorithm was developed and applied in order to test the performance and suitability of the approach for detecting water use events from flow sound at the outdoor tap. The automated algorithm was implemented in Visual Basic for Applications but included a dynamic link library written in C++ for reading WAVE files.

Sound files typically contain huge amounts of data that take too long to process directly. The audio signals were reduced by computing the short-term energy of a moving window of length 2.5 milliseconds. The magnitude of the short-term energy generally increases when water is flowing in the pipe (Fogarty *et al.* 2006; Jacobs *et al.* 2015). Prior to the transformation of the signal by short-term energy, a Chebychev high-pass filter was applied to the recordings to attenuate frequencies below 700 Hz, which comprised most of the unwanted sounds. The normalized short-term energy, also referred to as the power of the signal, was computed by Giannakopoulos & Pikrakis (2014):

$$E(k) = \frac{1}{W_L}\sum_{n=1}^{W_L}|x_k(n)|^2 \quad (1)$$

where k is the window number, n is the sample number, W_L is the window length and $x_k(n)$ is the audio sample at the kth position in window n.

Algorithm for change-point analysis

Change-point analysis was used to segment the signal. The goal of change-point analysis was to identify points in the signals where there were abrupt changes in the distribution of the short-term energy. Chen & Gupta (2011) have described a number of approaches that are commonly used for change-point analysis. In this study, the Schwarz Information Criterion (SIC) approach was adopted. The SIC method involves testing the null hypothesis that there is no change-point in a signal. The alternative hypothesis is that there is exactly one change-point in the signal.

Assuming a Gaussian distribution for the natural log transform of the short-term energy values with parameters (μ_1, σ_1), …, (μ_n, σ_n), the null hypothesis that was tested was:

$$H_0\colon \mu_1 = \cdots = \mu_n = \mu \text{ and } \sigma_1^2 = \cdots = \sigma_n^2 = \sigma^2$$

against the alternative hypothesis:

$$H_1\colon \mu_1 = \cdots = \mu_k \neq \mu_{k+1} = \cdots = \mu_n \text{ and } \sigma_1^2 = \cdots = \sigma_k^2 \neq \sigma_{k+1}^2 = \cdots = \sigma_n^2$$

where k is the location of the change point and n is the total number of samples. Chen & Gupta (2011) have presented a detailed derivation of the SIC approach based on the log likelihood functions under H_0 and H_1. The key formulae are given below. The SIC given no change point is calculated by:

$$SIC(n) = n \log 2\pi + n \log \hat{\sigma}^2 + n + n \log n \quad (2)$$

and the SIC assuming a change in mean and variance at any point k is calculated by:

$$SIC(k) = n \log 2\pi + k \log \hat{\sigma}_1^2 + (n-k) \log \hat{\sigma}_n^2 + n + 4 \log n \quad (3)$$

where the variances σ^2, σ_1^2 and σ_n^2 are estimated from the signal. The minimum SIC(k) is used to test the null hypothesis. A change point is considered to have occurred if:

$$SIC(n) > \min_{2 \leq k \leq n-2} \{SIC(k)\} \quad (4)$$

The location of the change point corresponds to the value of k that minimizes SIC(k). A binary segmentation algorithm as presented by Eckley *et al.* (2011) was then used to recursively apply the SIC change-point analysis procedure on the signal subsequences created at each step until no more change-points could be detected.

Automated detection of tap use events

Segments in which flow was present were detected from the change point analysis results by applying a short-term energy threshold. Recordings from the first week of the study period were set aside as training samples for the determination of appropriate short-term energy thresholds tailored for the study home (SH) at hand. The performance of the automatic algorithm was assessed by comparing the detected tap flow event times to the manually abstracted flow event times. For each study home, precision was calculated as the percentage of the total detected time that coincided with the manually abstracted event times. Recall was obtained by expressing the coincident event time as a percentage of the total flow time obtained manually. The detection algorithm was applied at various systematically adjusted short-term energy threshold values. The suitability of each threshold value was evaluated by the F score, calculated according to Equation (5):

$$F\ score = \frac{2 \cdot precision \cdot recall}{precision + recall} \quad (5)$$

The F score gives a harmonic mean between precision and recall commonly used to quantify the discrimination of classes by a classification algorithm (Polat & Güneş 2009). Higher values of the F score statistic are associated with better detector performance. The energy threshold value that gave the highest F score value was adopted and tested in the subsequent 3-week long sound recordings.

RESULTS

Waveform and spectrogram properties

In the absence of sound, the audio signal had a relatively low amplitude waveform. These sections were characterized by random noise normally referred to as 'white noise'. Ideal white noise is composed of all frequencies at generally equal levels. When played, these white noise segments had a clearly recognizable soft sound. The spectrograms for the silent segments of the signal were relatively sparse and uniform except for a slightly denser region in the low frequency band. Figure 2(a) shows a typical waveform and spectrogram for a white noise segment. The short-term energy signal was observed to follow a diurnal cycle with values that gradually increased during the day and dropped at night. The actual cause of the cyclic variation was not established but it is likely that the rise in noise level during the day and the increase in temperature of the tap branch pipe contributed to the observed variation. The magnitude of the diurnal change was, however, observed to be small in comparison to the changes caused by flow sound. The diurnal variation was therefore neglected.

Time periods when the tap was running were characterized by larger amplitudes in the signal waveform. Flow sound caused an increase in the color intensity of the spectrogram in the higher frequency bands. Unique horizontal bands could also be traced along the spectrogram which contrasted with other types of sounds in the signal. Figure 2(b) shows a waveform and spectrogram of flow sound for a tap with a hosepipe connected while Figure 2(c) shows the effect of running the water into a bucket. In many cases the onset of a tap use event showed a sudden and brief rise in the waveform amplitude, caused mainly by the rapid transition from low to high flow. The turning of the handle when opening or

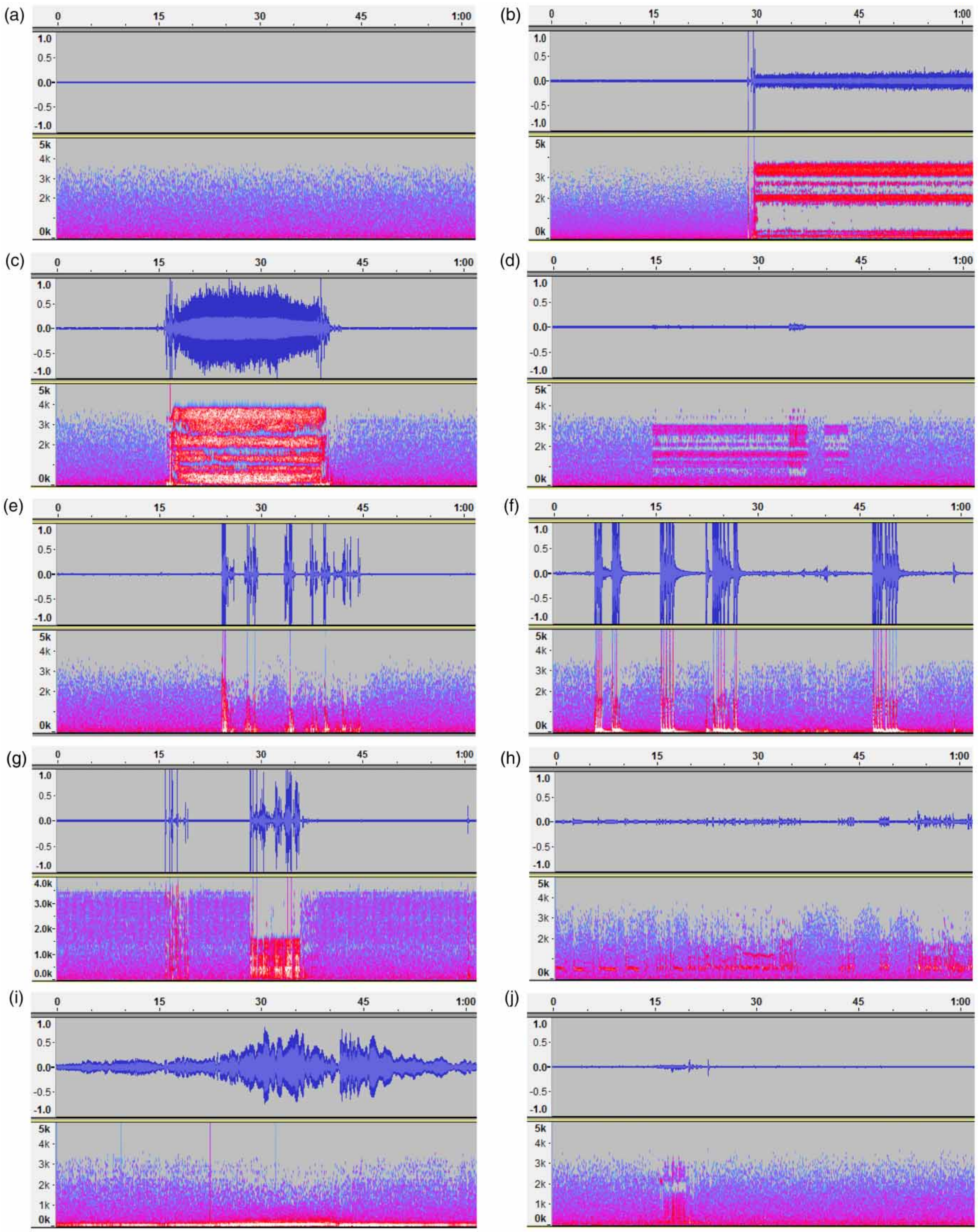

Figure 2 | Waveforms and spectrograms of (a) white noise section with no sound recorded, (b) water running through a hosepipe, (c) water run into a bucket, (d) an indoor water use event, (e) object hitting tap and nearby objects, (f) hammering near the tap, (g) object being pushed over the ground near the tap, (h) dogs barking, (i) heavy vehicle passing through a nearby road and (j) mobile phone interference.

closing the tap also contributed to the louder sound observed at the start and end of most events, which was useful in cases where other sounds had to be screened out. As might be expected, the splashing of water running directly from the tap into a bucket was usually loud enough to mask the onset transient. Figure 2(d) represents an indoor water use event that was recognizable at the outdoor tap. It can be noted that the waveform amplitude was small for indoor events and that the spikes normally present at the start and end of tap use events were virtually absent.

Sound is conducted reasonably well through solids. As a result, sounds from objects hitting the tap or other objects nearby the tap were present in the recordings. In the majority of the cases, these sounds created easily noticeable irregularities in the signal waveform and spectrogram. An exception to this observation was the sound of objects being moved over surfaces nearby the tap, which had a similar spectrogram to that of flow sound. These noises, however, were not problematic because they were infrequent, only lasted for brief moments and were easy to distinguish audibly. Figure 2(e)–2(g) show the waveforms and spectrograms for the sound of an object hitting the tap, sound of hammering nearby the tap and an object being pushed over the ground near the tap respectively.

While there was not much indication of airborne sound in the recordings, the rubber microphone coverings did not seem effective at blocking loud and high pitched airborne sounds. Speech sound, for example, was rarely noted in the recording while the sound of the barking of dogs, as shown in Figure 2(h), was found in most of the recordings. Occasionally, loose cable ties on the rubber coverings would open the microphone up to ambient noise but these cases were corrected soon after being discovered. Heavy vehicles passing by a nearby road generated intense but low frequency sound as shown in Figure 2(i). A mobile phone brought near the sound recorder could also cause interference in the audio signal as shown in Figure 2(j).

Comparison of manually extracted events and automatically detected events

The precision, recall and F score values obtained from the application of the automatic detection algorithm to the training and test data sets are given in Table 1. The detection algorithm performed well for SH1, SH2, SH3, SH4, SH5 and SH7. The high F score values for these homes were possible because the sound of flow in the recordings was generally louder, allowing higher energy detection threshold values to be used. Higher threshold values reduced false positives substantially, and contributed to overall good detection performance. On the contrary, the performance of the detection algorithm was poorer for homes that experienced low water pressure on a regular basis, typically during peak demand periods. According to the homeowners, SH8, SH9 and SH10 experienced significantly reduced water pressure during the morning. These three homes were located in the same neighbourhood near a stadium that was still under construction during the study period. It is likely that water pressure in the entire neighbourhood was affected by water use at the construction site. Lowering the threshold to detect the quieter flow sound in the recordings correspondingly increased false positives and reduced the precision.

The quieter sound of flow related to reduced pressure also presented challenges for the human operator labelling water use events. In some cases, the sound of flow would gradually fade in the course of a long water use event until the waveform and spectrogram closely resembled non-flow sections. One could classify these sections as flow when in fact the tap temporarily stopped running, or on the contrary,

Table 1 | Performance of the detection algorithm

	Training dataset			Test dataset		
Study home	Precision (%)	Recall (%)	F score	Precision (%)	Recall (%)	F score
SH1	92.4	92.5	92.4	97.2	82.4	89.2
SH2	96.1	100.0	98.0	96.0	99.9	97.9
SH3	75.9	96.7	85.1	77.6	94.8	85.3
SH4	97.2	99.3	98.2	93.0	96.1	94.5
SH5	98.7	98.7	98.7	98.6	99.0	98.8
SH6	83.2	77.9	80.5	88.2	68.5	77.1
SH7	97.6	98.9	98.3	98.5	91.0	94.6
SH8	51.5	82.6	63.4	78.2	68.7	73.1
SH9	59.8	49.7	54.3	81.7	37.5	51.4
SH10	63.2	88.7	73.8	67.9	80.1	73.5

there could merely have been a transition from loud and turbulent flow to quiet and smooth flow following a drop in flowrate. In the manual analysis, if the waveform, spectrogram or audible sound did not indicate flow, the corresponding segment was not labelled as flow even if it occurred between tap open and close events. Overall, the characterization of flow sound was less precise at low flowrates.

At SH6 and SH9, the outdoor tap was located between the water consumption meter and the house. Many events detected in the automatic algorithm lacked the noise of the tap open and close features shown in Figure 2(d), except that the amplitude of the waveform was larger. It was suspected that the outdoor tap standpipe branched off directly from the pipe running into the house so that the sounds of indoor water use events were just as loud in the recordings. The application of the simple energy threshold based technique alone did not effectively separate the sound of indoor water use events from the outdoor tap water use events, leading to reduced F scores at these two homes.

Outdoor water use characteristics

Figures 3 and 4 are presented to show the general pattern of water use at the outdoor taps of the study homes for the period analyzed. The summaries were limited to the study homes that had an F score of at least 85% in the test data detection results. SH6, SH8, SH9 and SH10 were therefore excluded in the results presented in Figures 3 and 4.

Although the study was targeted at water used for garden irrigation, most of the homeowners had indicated other uses of the outdoor tap that are ordinarily associated with indoor use, for example washing clothes or cleaning the house. Figure 3 presents the frequency distribution of the outdoor tap water use events according to duration, plotted on a logarithmic scale. At least 50% of all the water use events lasted 1 minute or less, indicating significant use of the outdoor tap for purposes other than irrigation at the homes where a hose pipe was used for irrigation.

Figures 4 and 5 show the diurnal tap use pattern during weekdays and on weekends respectively. The horizontal

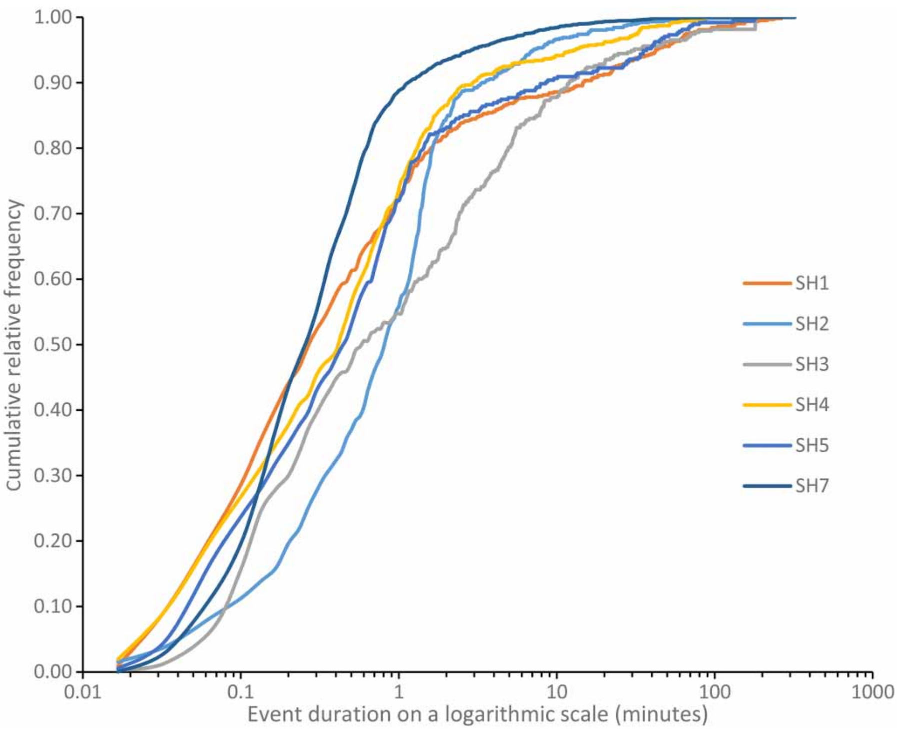

Figure 3 | Frequency distribution of tap water use events by duration.

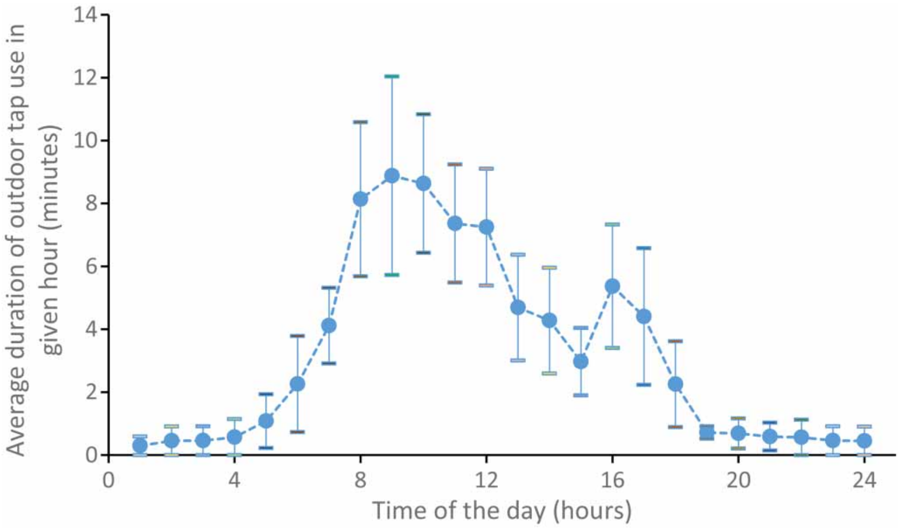

Figure 4 | Diurnal water use pattern during weekdays.

axis represents the time of the day in hours while the vertical axis represents the total duration the tap was running during each respective hour averaged over the 1-month study period and the study homes. Generally, peak water use at the outdoor tap occurred between 8 and 11 am. Pressure at the outdoor tap is likely to vary with time throughout the day and from one household to another. As a result, the duration of tap use shown in Figures 4 and 5 does not exactly represent the intensity of water use. The two figures, however, portray periods during the day when most outdoor tap use activities occur.

DISCUSSION

Privacy issues

It is likely that continuously recording sound, as was the case in this study, could potentially intrude into personal privacy of the homeowners. Presumably, recording speech sound would particularly raise concerns among many people. Besides privacy issues, continuous recording creates large files which dramatically increase storage requirements and computer processing time. The use of a barrier to block

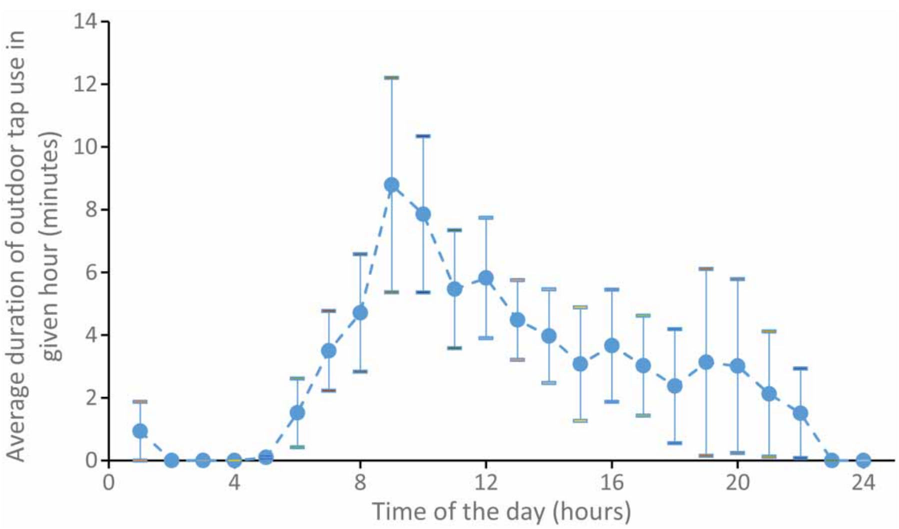

Figure 5 | Diurnal water use pattern on weekends.

sounds, as in this study, may not sufficiently protect the homeowners' privacy. Another measure could be the use of custom designed modules that are configured to sample short durations of sound at intervals that render critical sounds, speech for instance, indecipherable. A similar configuration was used by Fogarty *et al.* (2006), though not for privacy reasons, with the benefit of low disk storage requirements. Alternatively, the signal could be preprocessed so that only the parameter values of interest are stored.

Further research

This study focused on detecting the start and finish times of the outdoor tap water use events. Some reported studies suggest the potential for estimating the flowrate from the flow induced sound or vibrations. Evans *et al.* (2004) have demonstrated that pipe flowrate is strongly correlated to the variance of the noise of audio signals from the pipe. Kakuta *et al.* (2012) developed a relationship between flowrate and the sound pressure level. Jacobs *et al.* (2015) have also shown correlation between flowrate and the amplitude of the peak modus frequency of the sound of a tap. However, these techniques are unlikely to achieve a similar performance for sound recorded at the outdoor tap because the flow induced sound usually mingles with other sounds, such as the running water striking the ground or splashing into a container. Additional challenges include the effect of pipe material, pipe size and age, as well as tap configuration. Further research is required to evaluate the accuracy of flowrate estimates that can be achieved for sound of flow at the outdoor tap. Apart from analytical methods used in the studies above, learned probabilistic models are a potential area that could be exploited to improve the performance of these techniques.

CONCLUSIONS

This paper presented findings from the use of sound to deduce the start and finish times of water use events at the outdoor tap. The analysis was performed on 1-month long sound recordings from the outdoor tap at 10 study homes. Flow sound was noted to have distinct spectral properties that were easily recognizable when the sound waveform was displayed as a spectrogram. The detection of water use events from the recordings was effectively automated by an SIC based segmentation algorithm and the application of a customised short-term energy detection threshold. The approach described is a low-cost alternative to smart metering that is especially suited to the study of outdoor water use.

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