Ad Hoc Networks 11 (2013) 1456–1471

Contents lists available at ScienceDirect

Ad Hoc Networks

journal homepage: www.elsevier.com/locate/adhoc

SewerSnort: A drifting sensor for in situ Wastewater Collection System gas monitoring

Jung Soo Lim [a], Jihyoung Kim [a], Jonathan Friedman [b], Uichin Lee [c,*], Luiz Vieira [d], Diego Rosso [e], Mario Gerla [a], Mani B. Srivastava [b]

[a] UCLA CS, United States
[b] UCLA EE, United States
[c] KAIST KSE, Republic of Korea
[d] Federal University of Minas Gerais, Brazil
[e] UCI CEE, United States

ARTICLE INFO

Article history:
Available online 23 March 2011

Keywords:
Wastewater Collection System
Biochemical process
Electrochemical gas sensor
Received signal strength indicator based localization
Mobile sensing

ABSTRACT

Biochemical reactions that occur in sewer pipes produce a considerable amount of hydrogen sulfide gas (H_2S corrosive and poisonous), methane gas (CH_4 explosive and a major climate change contributor), carbon dioxide (CO_2 a major climate change contributor), and other volatile substances (collectively known as in-sewer gases). These toxic gases lead to contamination of natural environment, sewer pipe corrosion, costly operational expense, public safety issues, and legal disputes. In order to prevent biochemical reactions and to maintain healthy sewer pipes, frequent inspections are vital. Thus far, various schemes have been designed and developed to identify functional deficiencies in Wastewater Collection System (WCS). Nevertheless, the current inspection techniques are not for mapping the sewer gas concentration. In addition, because of such a harsh and hazardous environment a comprehensive sewer gases inspection has been prohibitively expensive.

In this paper we propose SewerSnort, a low-cost, unmanned, fully automated in-sewer gas monitoring system. A sensor float is introduced at the upstream station and drifts down sewer pipeline, while the sensor float collects gas measurements along with location information of sampling points. At the end of the journey, the gas measurements are retrieved from the float and used to generate gas concentration to be used for maintenance or repair. The key innovations of SewerSnort are the fully automated, end-to-end monitoring solution and the low energy self localizing strategy. From the implementation standpoint, the key enablers are the float mechanical design that fits the sewer constraints and the embedded sensor design that matches the float form factor and complies with the tight energy constraints. Experiments based on a dry land emulator demonstrate the feasibility of the SewerSnort concept, in particular, the localization technique and the embedded sensor design.

1. Introduction

A Wastewater Collection System (WCS) collects and transports wastewater generated from households and industries to treatment plants or disposal sites by means of a system of underground pipelines. During the

* Corresponding author. Address: Department of Knowledge Service Engineering, KAIST 291 Daehak-ro, Yuseong-gu, Daejeon 305-701, Republic of Korea. Tel.: +82 42 350 1616; fax: +82 42 350 1610.

E-mail addresses: jlim@cs.ucla.edu (J.S. Lim), jhkim@cs.ucla.edu (J. Kim), jf@ee.ucla.edu (J. Friedman), uclee@kaist.ac.kr (U. Lee), lfvieira@dcc.ufmg.br (L. Vieira), bidui@uci.edu (D. Rosso), gerla@cs.ucla.edu (M. Gerla), mbs@ee.ucla.edu (M.B. Srivastava).

1570-8705/$ - see front matter © 2011 Published by Elsevier B.V.
doi:10.1016/j.adhoc.2011.01.016

transportation process a periodic inspection and maintenance of sewer pipe must be performed particularly for aging pipes reaching or past its life expectancy since WCS components are prone to damage from aging, excessive traffic, and biochemical reactions [6]. In addition, untreated sewer escaped from WCS through leaks or overflow endangers public health by contaminating the source of drinking water and polluting natural environment [5].

Organic material transported by the sewer accumulates along the bottom (forming a sediment), and walls (forming a coating known as "bio-film"), of the pipeline. Due to anaerobic conditions, where insufficient electrons are available to accept ions, biochemical reactions that occur in these sediments and bio-film generates substantial amount of hydrogen sulfide (H_2S), methane (CH_4), and other volatile substances (collectively, in-sewer gases) [13]. Hydrogen sulfide, which is toxic and odorous gas, is a precursor to the formation of sulfuric acid (H_2SO_4) which is corrosive to metal and concrete and noxious to human [48]. On the other hand, methane gas is highly flammable and forms explosive mixtures with air. Also, methane gas is an asphyxiant and may displace oxygen in an enclosed space [38]. In addition, there is growing consensus that sewage systems contribute a significant fraction of greenhouse gases (GHG) such as carbon dioxide (CO_2) and methane [34,10].

Due to such an unfriendly and harsh environment direct sewer inspection and maintenance operations are life-threatening. A number of complicated and expensive indirect methods has developed in the past. For example, *pipe leakage detection* can be accomplished via the injection of smoke and fluorescent dyes [42,33] or via remote inspection with cameras and sonar systems attached to tethered probes [42] or mobile robots [1]. *Sewer flow monitoring* can be achieved by installing flow meters at strategic locations so that the drainage system can be properly controlled to prevent or to minimize overflows [43]. Also, *sediment control* can be accomplished via localized flushing or chemical treatments [5].

While pipe damage detection and flow monitoring have been actively studied in both academia and industry, in-sewer gas monitoring has received little attention due to the difficulty of in situ measurements and the relative lack of sensor installations – mostly in treatment plants. Also, areas that are easily approached and instrumented are principally limited to manholes. However, manhole-based sensor readings are poor indicators of toxic gas concentration due to the fresh air flowing through the manhole (called the "chimney effect"). To fill the gap the United States Environmental Protection Agency (USEPA) recommends an analytical modeling to predict sediment buildups and gas concentrations [5]. Nonetheless, it is extremely difficult to model and fit a sewer system due to the large spatio-temporal variability and the lack of legitimate data. To this reason, a proper maintenance is not usually performed, or rather sewer flushing is performed only when odor complaints are received or legal disputes are occurred which results endangering public health and causing expensive litigations [2].

Thus, there is a strong rationale for in-sewer gas monitoring especially when sewer gas is a key indicator of sewer conditions (sediment buildups, corrosion, and explosion) [13]. Also, accurate and effective sewer gas monitoring can suggest areas for targeted supplemental study or corrective actions. In addition, the accurate information of toxic gases can reduce the occupational health and safety risks of personnel working in sewer pipes. As in-sewer fiber optical cable installations become prevalent, the safety issues become more of concern [49]. Moreover, researchers can have a better understanding in-sewer gas phases and can estimate accurate amount of GHG production in sewers [34,10].

In this paper, we design a low cost in-sewer gas monitoring system. The proposed system would allow frequent WCS inspection, comprehensive WCS sewer gas measurement, and early detection of problems. In addition, the system allows targeting of accurate sewer flushing measure which substantially improves service uptime, reduces the maintenance expense, enhances illegal toxic chemical dumping enforcement, reduces the risks of contaminating the source of drinking water, and reduces the risks of polluting our natural environment.

To this end, we propose SewerSnort, a novel method involving drifting sensors that monitor in-sewer gases. A SewerSnort node is dispensed upstream of the WCS. It measures in-sewer gas concentrations while floating downstream and marks measurement readings along with their geographic location obtained from a set of beacons located beneath manholes. Upon the completion of journey, a SewerSnort node is extracted at a wastewater treatment plant, pumping station, or sewer manhole. The data acquired by SewerSnort can be collected through traditional public network infrastructure systems such as municipal Wi–Fi, an emerging low-power high-availability mesh networking system such as Streetline [40]. Additionally, the data in SewerSnort can be manually retrieved through short-range wireless communication upon retrieval since physical contact with the probe once deployed in the sewer is not advisable due to surface contamination and biohazard.

In this paper, we make the following contributions to the field:

- We show the feasibility of a mobile drifting sensor by analyzing the sewer flow statistics and present the potential applications of in-sewer gas monitoring.
- We design an "inner-tube" shaped hull to handle the lateral force that pushes the drifter to the side of the sewers (known as the bank suction effect).
- We present the first single-supply differential ratiometric data acquisition architecture that targets electrochemical sensors for WCS monitoring applications. The design is implemented and evaluated. Controlled experiments confirm the accuracy of our gas sensor module.
- We propose a Received Signal Strength Indicator (RSSI) based localization scheme that provides meter-level accuracy in the underground GPS-denied sewer environment. Over ground experiments based on a programmable mobile robot emulator confirm the viability of proposed method.

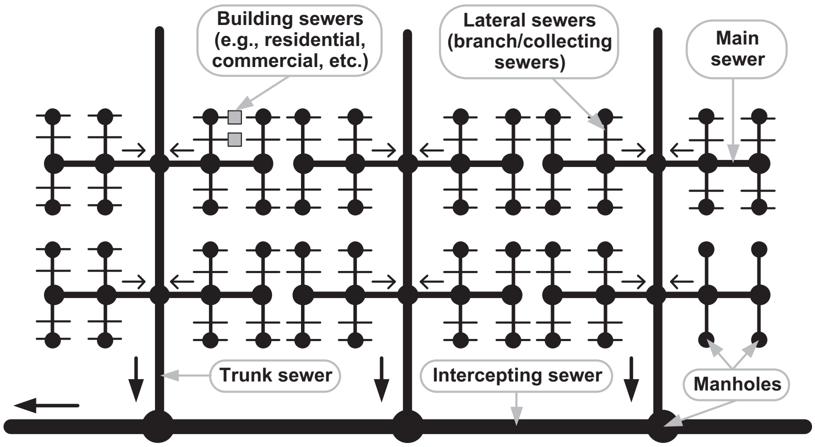


Fig. 1. Illustration of a sewer system.

This paper significantly enhances our earlier work [17] as follows. First, we include the description of environmental/health impact of sewer gas (Section 2). Second, we provide a detailed description of ratiometric signal conditioning (Section 4). Third, we elaborate the enhancement scheme for location estimation using flow velocity and discuss a method of handling the case when a beacon is unreachable or failed (Section 4.3). Fourth, we analyze the storage space requirement of SewerSnort (Section 4.4). Fifth, we discuss mechanisms for fault recovery using a convoy of drifters (Section 4.6). Finally, we present possible research directions such as drifter mobility modeling and networked drifters (Section 7).

2. Background

2.1. Wastewater Collection System

A Wastewater Collection System collects wastewater generated from households or industries and transports them to treatment facilities or disposal sites. The system is categorized as a separate sewer system or a combined sewer system depending on whether sanitary wastewater is separated from storm water. The separate sewer system has two wastewater drainage systems in parallel; i.e., a sanitary sewer discharging wastewater to a wastewater treatment plant and a storm sewer discharging storm water to a receiving water basin.[1] The combined sewer system drains both sanitary and storm water to a wastewater treatment plant. There are two types of sanitary sewers based on hydraulic characteristics and purposes: gravity and pressure sewers. The gravity sanitary sewers transport wastewater by gravity and are commonly used to collect wastewater from wastewater sources (residential, commercial, industrial sources). Gravity sewers are used when the natural slopes are sufficient enough to convey a flow. The pressure or pumped sewer transports wastewater using pressure to collect wastewater from residential sources where the construction of a gravity sewer is unsuitable (e.g., uphill slopes). It is also possible to use a combination of gravity and pressure sewers.

A typical separate sanitary collection system illustrated in Fig. 1 is organized as follows:

- *Lateral sewers* (also called branch or collecting sewers) are used to collect wastewater from buildings (entry points) and convey it to the main sewer. They are usually located underneath streets or utility easements.
- *Main sewers* are used to convey wastewater from lateral sewers to larger sewers (trunk or intercepting sewers).
- *Trunk sewers* are large sewers that are used to convey wastewater from main sewers to the treatment or disposal facilities or to large intercepting sewers.
- *Intercepting sewers* are large sewers that are used to intercept a number of main and trunk sewers and convey wastewater to the treatment or disposal facilities.
- *Manholes* are used for sewer cleaning and inspection. They are located where the pipe system changes direction, grade, or diameter, at junctions, and, for small diameter sewers (d < 1.2 m) at intervals no greater than 120 m.

2.2. In-sewer processes

In-sewer processes that occur during conveyance of wastewater are physical, chemical and biological in nature. Physical processes are related to the buildups and erosion of sewer sediment. Chemical and physico-chemical processes occur due to the gas transfer over the air-water interface (e.g., emission of hydrogen sulfide) and the chemical oxidation and precipitation of sulfide. In biological processes, bacteria degrade organic compounds, such as formaldehyde (CH_2O), obtain carbon for cellular growth/reproduction and energy for cellular activity. As a result, wastewater compounds are transformed and the biodegradability of the wastewater is changed.

As shown in Fig. 2, in-sewer biological processes happen in five phases [13]: suspended water, bio-film (slime layer), sediment, atmosphere, and the sewer wall. These phases interact and exchange relevant substances across

[1] A receiving water basin denotes a stream or river that has water flowing in it, or a lake, pond, dugout, or slough that has water standing in it.

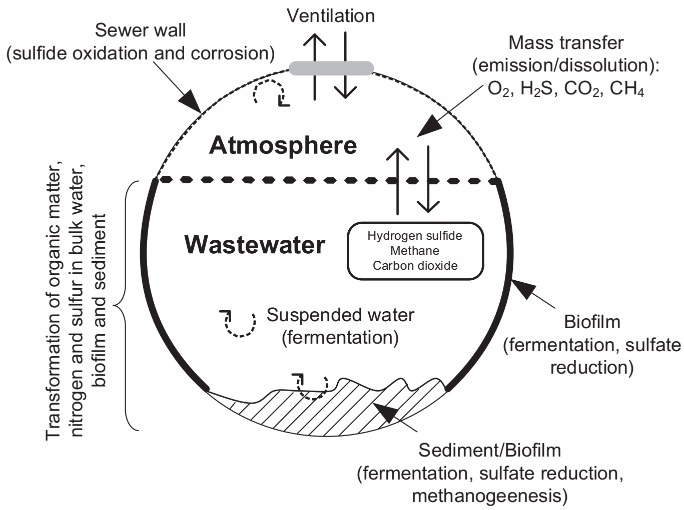


Fig. 2. Illustration of in-sewer processes.

Table 1
Sewer gases under different redox conditions.

Redox conditions	Possible Sewer Types	Sewer Gases
Aerobic (+oxygen)	Partly filled gravity sewer	Carbon dioxide (CO_2)
	Aerated pressure sewer	
Anoxic (−oxygen, −nitrate)	Pressure sewer with nitrate	Carbon dioxide (CO_2)
Anaerobic (−oxygen, −nitrate, +sulfate)	Pressure sewer	Hydrogen sulfide (H_2S) [*sulfate reduction*]
	Full-flowing gravity sewer	Carbon dioxide (CO_2) [*fermentation*]
	Gravity sewer (low slope, sediment)	Methane [*methanogenesis*]

the phase boundaries. An in-sewer bio-process will have different behavior based on microbial redox conditions: aerobic respiration when dissolved oxygen is present, anoxic respiration when nitrate/nitrite ions are present and anaerobic respiration when none of these (oxygen, nitrate/nitrite ions) are present.[2] In Table 1, we summarize different redox conditions and relevant sewer gases generated in various types of sewers. Aerobic/anoxic respiration produces carbon dioxide, whereas anaerobic respiration generates numerous volatile substances that vaporize or evaporate at atmospheric pressure such as hydrogen sulfide (product of sulfate reduction), carbon dioxide (product of fermentation), and methane (product of methanogenesis).

In particular, hydrogen sulfide diffused into a thin liquid film on the sewer surface (see Fig. 2) can be oxidized to sulfuric acid (H_2SO_4) by microbial reactions [13]. Then, sulfuric acid may react with the alkaline cement ($CaSO_4$) in the concrete pipes causing corrosion.

Each of these in-sewer processes can be analytically modeled using differential equations [45,50]. The models typically consider various factors that influence reactions [45]. For instance, a sulfate reduction model takes the following factors as inputs: quantity of sulfate, Chemical Oxygen Demand (COD), temperature, pH, area-to-volume ratio (i.e., bio-film and sediment), flow velocity, and anaerobic residence time [50].[3] In practice, however, accurately fitting a model to in-sewer processes is greatly challenging, for the present approaches make in situ measurement extremely laborious and substantial data collection must be performed to count and to understand the spatio-temporal variability of the underlying model parameters while biological processes are correlated [45]. Understanding the overall sewer reactions in sewers is a challenging area of active interest in the urban water research community. Note that the goal of this paper is not to accurately estimate the model parameters of in-sewer processes, but to directly observe the behavior of various gas phases and to predict their potential impact on sewer maintenance and green-house-gas emission given the sewer structure.

2.3. Environmental and health impacts of sewer gas

High concentration of sewer gas is a warning signal of system failure that initiates hazardous environments (i.e. endangering public health and contaminating our natural environment). Sewer gas not only generates obnoxious malodors, but also contains harmful toxic gases such as hydrogen sulfide and carbon dioxide which endanger public safety. Moreover, by considering the growing consensus

[2] A microbial "respiration" process consists of two steps (called redox process): *oxidation* of organic matter and *reduction* of an electron acceptor. In other words, bacteria break down organic matter and transfer electrons from the electron donor (organic matter) to the relevant electron accepter (e.g., oxygen, nitrate/nitrite ions, sulfate ions).

[3] Chemical Oxygen Demand (COD) is defined as the quantity of a specified oxidant that reacts with a sample under controlled conditions.

that sewer gas represents a significant fraction of GHG, the sewer gas substantially pollutes our natural environment.[4] However, the current effort to quantify GHG emissions from wastewater conveyance and treatment industries has largely overlooked the sewers because of the lack of basic knowledge about sewer internal dynamics and access limitations of the current sewer inspection technologies. Especially when we consider the fact that a significant fraction of wastewater components nowadays (e.g., soaps, detergents) are petrochemical derivatives with definite impact on GHG, acquiring accurate gas concentration distributions in sewer becomes more critical than ever before.

Up until now the current sewer models have been based on punctual measurements of methane gas, with immense loss of the opportunity of measuring a suite of components throughout the sewer network. Thus, the proposed method to solve this important environmental problem makes it feasible to probe the entire WCS and to overcome the limits of current sewer gas emission models that rely only on punctual measurements.

3. SewerSnort system overview

3.1. System design requirements

Our main goal is to design an in-sewer gas monitoring system that considers the following requirements:

- *The system should be independent of pipe profile* (material, shape, or size). The most widely used image capture technologies such as Closed-Circuit Television (CCTV), Sewer Scanner and Evaluation Technology (SSET), and sonar only work with a limited set of the pipe materials and shapes deployed in WCS's [42].
- *The system should be scalable*. A large metropolitan city like Los Angeles has a WCS composed of over 12,000 km of pipelines [28].
- *The system should be able to access the entire extent of the WCS*. All current physical assessment methods are limited to a comparatively small travel distance from their access point into the WCS.
- *The system should be fielded with reasonable cost* such that the deployment, maintenance, and operational expenses allow for near continual redeployment. At present, CCTV inspection costs \$2.26/foot and SSET inspection costs \$3.47/foot. For the city of Los Angeles it could cost upwards of \$12.7 million USD to perform a single comprehensive inspection. A reduction of at least two orders of magnitude for an entire year of deployments is desired [31].

3.2. SewerSnort: gas monitoring using drifting sensors

We propose SewerSnort, a drifting sensor which monitors in-sewer gases (Fig. 3). Knowing that small sewers are typically under the aerobic redox condition and do not produce gases of interest (hydrogen sulfide and methane), we

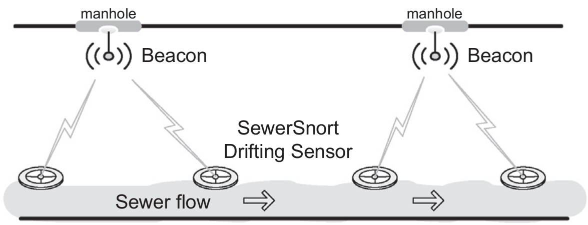


Fig. 3. SewerSnort monitoring scenario.

mainly provide inspection coverage to main, trunk, and intercepting sewers of WCS. During the deployment, SewerSnort dispensers are deployed at strategic locations by analyzing the sewer map and inspection demands. The strategic points are typically located at an entry point to the sewer. SewerSnort dispensing schedule can be configured based on the application scenario. For instance, if engineers want to understand how in-sewer gas level changes over time, they can dispense drifters at regular intervals for continual sampling.

Once a drifter is deployed, we need to keep track of its position. Since the Global Positioning System (GPS) transmits signals from very high altitudes using only 50 W transmitters by microwave-frequency carriers, the GPS signal does not readily penetrate the ground. Thus, we propose a GPS-free localization scheme by exploiting beacons and Received Signal Strength Indicator (RSSI). First, preprogrammed beacons are installed under sewer manholes in the region of interest. Then, beacons broadcast messages which include their physical locations and timestamps by pre-determined interval. Second, a SewerSnort listens to the beacons and collects RSSI values from received beacon messages, when traversing down pipes. Then, a SewerSnort estimates its proximity based on beacon messages and the strength of their respective signals (via off-line processing).

The main advantage of sewer drifters is their immunity to pipe profile. It is neither sensitive to the materials nor dependent on the shape of a sewer pipe. Yet, they compare favorably in other metrics as well. Conventional robotic systems are bulky, heavy, and require sufficient flow rate, external power, or internal power generation [24]. SewerSnort drifters are small, light, and battery-operated (e.g., <30 cm in diameter, and <0.5 kg in weight) and can operate during low flow rate conditions.

3.3. Feasibility of drifting sensors in sewers

The fluid flow in a pipe is classified as either laminar (a stable and streamlined flow) or turbulent (a highly irregular and random motion). To determine the type of flow we use its Reynolds number, i.e., $Re = \rho\upsilon\delta/\gamma$ where ρ is the fluid density, υ is the fluid velocity, δ is geometrical length associated with flow, and γ is the viscosity that characterizes the degree of internal frictions in the fluid.

We consider the sewer flow to be laminar based on the following facts. First, sewers contain a high concentration of suspended solids which create great internal frictions and decrease the flow velocity. The concentration of suspended solids in a sewer has not been systematically

[4] According to New York Mayor's report in 2007, 17% of GHG emission was caused by sewer [26].

measured. However, approximately 100 milligram per liter (mg/l) of suspended solids exists in the effluent after the primary treatment in the wastewater treatment plant, while the tap water contains less than 1 mg/l [46]. Second, the gravity slope of most pipelines is rather mild to control the flow velocity, thus preventing sewer erosion. For instance, the sewer design manual of Bureau of Engineering at Los Angeles specifies 0.003 radian (or 0.1719°) for the pipe slope [37]. Third, concrete, which creates relatively more internal friction than copper, plastic or iron, is the most widely used material for sewer pipelines [5]. According to the Nikuradse's definition of mean height of roughness; copper and glass are 0.003, iron is 0.15, plastic is 0.03, and concrete is 6.0. Here, the larger the number, the higher is the roughness of surface. Thus, the sewer flow can be classified as laminar; in other words, it is steady and stable enough not to significantly affect in situ gas measurement.

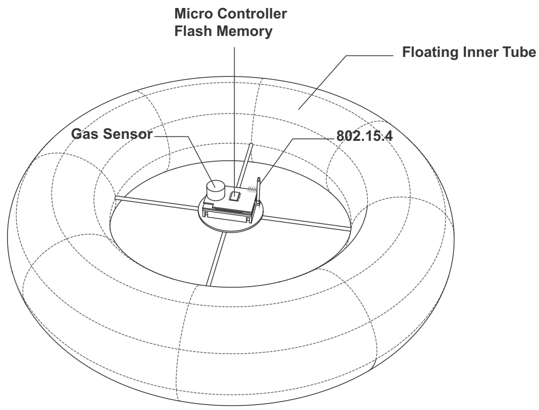


Fig. 4. SewerSnort drifter design. The size of a tube can be adjusted based on the size of pipe.

4. SewerSnort system design

4.1. Hull design

When a surface vessel moves through a constricted waterway, the current velocity gradient pushes the craft toward the nearest bank ultimately resulting in a collision. Our drifter will suffer from this phenomenon, known as the "bank suction" effect [7]. As our drifter approaches the sewer wall the water channel size reduces and in turn increases the velocity of the water on that side. The asymmetric flow around the drifter causes pressure differences. As a result, a lateral force will push the drifter to the side of the pipeline. The drifter will bounce against the wall as it lacks any on-board motion control. We propose an inner tube hull that can roll along the pipeline sidewall (Fig. 4). The sensing unit is placed in the middle of the inner tube to prevent wastewater from submerging it and the hull is tall enough to sustain the sensor above waterline in the event high turbulence capsizes the drifter.

4.2. Gas sensing unit

4.2.1. Electrochemical gas detection

Electrochemical sensors detect a particular Gas Of Interest (GOI) by reacting with it and producing an electrical current proportional to the gas concentration. This current is developed between the sensor's anode and cathode electrodes (Fig. 5) as one is oxidized and the other reduced. The exact chemistry is specific to the construction of the sensor and the GOI. In the following, we focus on hydrogen sulfide gas sensing, as it is one of the key sewer condition indicators.

Our SewerSnort drifters are equipped with an RAE 032-0102-000 electrochemical sensor element [32] and a custom Analog Front End (AFE) that provides bias and signal conditioning functions. The oxidation reaction that takes place at the anode is:

$$H_2S + 4H_2O \rightarrow H_2SO_4 + 8H^+ + 8e^-. \quad (1)$$

Note that the inputs include water. It is provided inside the sensor as an electrolyte into which the electrodes are immersed and sealed in by a gas-permeable hydrophobic membrane (Fig. 5). Besides sealing in the electrolyte (water is repelled from the membrane – hydrophobia) and offering mechanical protection to the sensor, the membrane performs the additional function of filtering out unwanted particulates. A scrubber filter of activated charcoal is installed in front of the membrane to further enhance the sensor's selectivity (the sensor's preference for the GOI over other look-alike gasses).

These internal design choices reflect a fundamental tradeoff between the selectivity (ability to target just the GOI – allow fewer molecules in) and the sensitivity (encourage as much reaction as possible – allow more molecules in) of the sensor. Given that the detection reactions are basic public chemistry, the design of the capillary, choice of the filter material, and the shape of the electrodes are the most important differentiating elements among commercial vendors and, correspondingly, these are the design aspects most heavily patented. Careful attention should be paid to application requirements when selecting a vendor. With SewerSnort we chose an element with very high selectivity and moderate sensitivity.[5]

4.2.2. Power concerns

It is important to have a stable and constant voltage at the anode electrode (w.r.t. the cathode), because, unaided, the voltage will fluctuate as the reaction taking place on its surface is continuously introducing mobile charges. These fluctuations void the calibration curve as the voltage changes in the electrolyte correspond to energy storage instead of a conversion to an electrical current which may be sensed. However, the SewerSnort drifters are battery-powered and must remain small, light, and inexpensive – precluding the use of large battery packs. Although, the use of modern Switch-Mode Power Supplies (SMPS) can achieve near 90% efficiencies, a SMPS must operate continuously to maintain the regulated output voltage conditioning the electrodes. Given that the SewerSnort drifter must travel an enormous distance (compared to

[5] The data sheet of RAE 032-0102-000 [32] reports that it is highly selective against carbon monoxide, nitric oxide, hydrogen, etc.

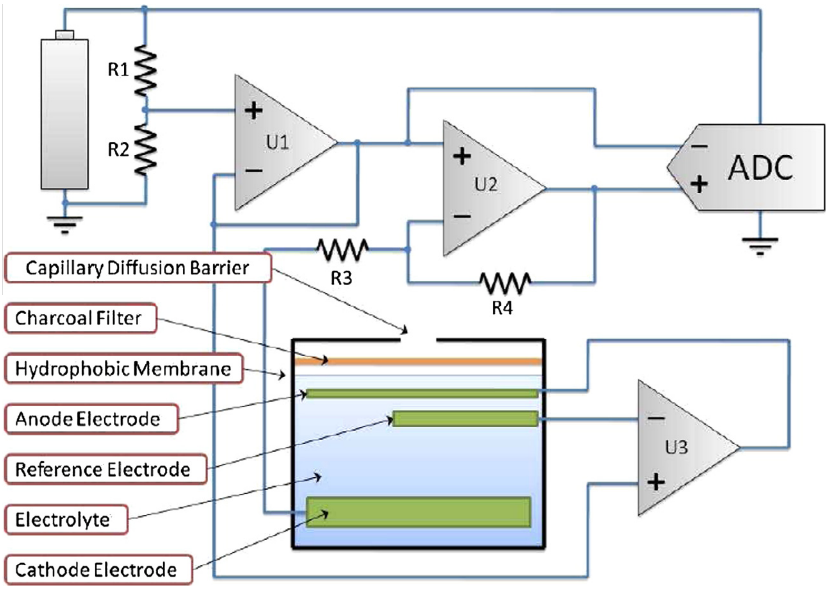


Fig. 5. A simplified schematic of the electrochecmical gas sensor and analog signal conditioning elements. This differential ratiometric approach consumes <15 μW in our current implementation. Electromagnetic compatibility elements are not shown for clarity.

its own dimensions) and do so at slow speeds (due to low flow rate), it will take measurements at a very low sample rate. During the inter-sample interval, the sensor electronics will be idle, and minimizing power consumed in this "sleep" state is substantially more important than minimizing active sampling power. This presents the drifter design with a difficult tradeoff: Regulate the sensor power supply to stabilize the operating conditions and hence ensure the accuracy of the sensor's calibration, but risk battery exhaustion, or allow the voltage to drift, empower data collection over the entire trip, but compromise the sensor calibration and, therefore, collect potentially meaningless data.

4.2.3. Ratiometric signal conditioning

In this work we explore an alternative that proffers to circumvent the conflict between calibration accuracy and power consumption and in the process present the first single-supply differential ratiometric data acquisition architecture that targets electrochemical sensors for WCS monitoring applications. To maintain the sensor's calibration curve the sensor must experience a nominal 0 V bias

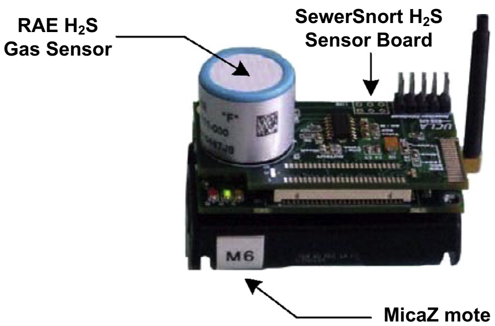


Fig. 6. The SewerSnort gas sensor board with a MicaZ mote.

condition ($V_{anode} = V_{cathode}$ for $I_{electrolyte} = 0$) and the amplifier must have sufficient dynamic-range (head room) to handle the increasing voltage of the amplified output. To meet these two conditions without the use of a power supply, we connect the amplifiers directly to the battery in a single-sided configuration (no negative voltage provided). An intermediate reference voltage is generated that is an arithmetic ratio of the battery voltage (in our implementation we used a ratio of $\frac{1}{2}$). This ratiometric reference potential is routed to both the transconductance amplifier responsible for sinking current from the cathode and the feedback amplifier responsible for driving the anode. As both terminals of the sensor are biased by the same potential, absent charge injection from a reaction (no GOI present), the 0V condition is achieved. As the battery voltage decreases over its cycle life, the reference voltage decreases as well preserving the amplifiers head room.

4.2.4. Implementing signal conditioning

Series resistors R_1 and R_2 form a voltage divider delivering $\frac{R_2}{R_1+R_2}$ percent of the battery's native voltage to the voltage-follower amplifier U1. The choice of values for R_1 and R_2 are controlled to achieve two objectives – minimize quiescent power and obtain the desired divider output voltage.

Achieving the former requires the use of large valued resistors which are limited only by the constraint:

$$\frac{V_{battery,max}}{R_1 + R_2} \gg I_{U_1,bias} \quad (\text{e.g.} > 10\ I_{U_1,bias}), \tag{2}$$

where $V_{battery,max}$ is the battery voltage when fully charged and $I_{U_1,bias}$ is the input bias current of the U_1 amplifier. Due to the mass trasport requirements (diffusion, limited aperature, catalytic conversion) inherent in electrochemical sensing, its transient performance is rather poor. For the chosen sensing element, the 10–90 response time is

30 s [32]. At this bandwidth, low-frequency, low-bias, operational amplifiers with Junction Field Effect Transistor (JFET) based input architectures are ideally suited. [22] from Microchip Corporation is an example of this type of amplifier. Over the industrial temperature range its input bias current requirement is a mere 0.1 nA. Accordingly Eq. (2) indicates that $R_1 + R_2$ could be as large as *300 Gigaohm* when supplied from a *3 Volt* battery. However, as resistance increases its Johnson thermal noise component increases as well. For a *300 Gigaohm* resistor this translates into a 22.5 μV offset at 0.1 Hz of bandwidth, but to achieve this performance the signal must be sampled contiuously over the 100 ms period. Microcontroller-based computer systems consume active power in the order of tens of milliwatts so supporting shorter sampling aperatures by increased sampling bandwidth requires the use of a smaller resistance to offset the increase in thermal noise from the increase in frequency. In our implementation we chose 10 Megaohm values as a good compromise.

The second design goal, orthogonal to the first, is to create a voltage somewhere in between the battery and ground. Given the known polarity of the redox reaction in the sensor cell, the AFE need not be equally adept at handling both positive and negative sensor voltage deviations. Electrons are generated at the anode and travel to the cathode. Due to the difference in convention between physicists and engineers, electron flow into a terminal will counter-intuitively raise the voltage of that terminal. However, the amplifiers, not being provided a negative voltage source, perform best when the signal is between its two power supply Voltages. In this case, that is equal to one-half of the battery's voltage and choosing $R_1 = R_2$ ensures this condition is realized and maintained during operation.

As the sensor operates, the voltage at the cathode increases, but the anode may fluctuate as well (as previously discussed). Amplifier U_3 provides a Reference-Anode feedback drive to ensure that despite U_1 providing a positive voltage $\frac{1}{2}$ the battery's, from the sensor's perspective the potential difference (voltage) anode-to-cathode is effectively 0. This bias condition is necessary to preserve the sensor by not artificially inducing the redox reaction. U_2 functions as a current mirror with a 1000-fold gain. These values were chosen in a manner similar to selecting R_1 and R_2 – by balancing similar noise floor constraints.

4.3. Localization

We build a radio-frequency (RF) based system to locate and to track a drifter. RF based localization has been widely used for indoor positioning via triangulation using measured signal strengths from multiple beacons [3,21]. We can use either an empirically measured signal strength map [3,21] or a theoretical model that captures signal attenuation over distance [3,29]. Recent measurement studies by Howitt et al. proposed a radio wave propagation model for concrete storm drain pipes in 2.4–2.5 GHz frequency band [11]. By using this model we estimate the location of the drifter inside the sewers. Unlike previous methods of "online" location tracking methods [3,21,29], we perform "off-line" signal processing on the measured signal strength samples to better estimate the trajectory of a drifter.

4.3.1. RSSI-based SewerSnort localization

To define a geospatial coordinate system RF beacons are embedded beneath manholes in the area of interest. The beacons broadcast their identity (i.e. geo-tag) periodically, which corresponds to a specific physical location.[6] Aboard a drifter the beacon message is heard and decoded to determine the beacon's identity while the average signal envelope power – the RSSI – is measured.

The relationship between RSSI and inter-radio distance may be approximated by the radio wave propagation model for concrete storm drain pipes as [11]:

$$RSSI(d)_{rx} = P_{tx} - \alpha_{(a,\sigma)} \times d - A_{CL}, \tag{3}$$

where $RSSI(d)_{rx}$ is the received power at distance d, P_{tx} is the transmitted power in dB, $\alpha_{(a,\sigma)}$ is the multimode attenuation loss (dB/m) which is dependent on radius (a) and conductivity (σ) of a concrete pipe, and A_{CL} is the antenna coupling loss given in dB. A value of A_{CL} changes based on a position of a beacon inside a pipe [11]. For example, if a drifter is located at the bottom of pipe, the value of A_{CL}, when a beacon is located in the center of pipe, is smaller than the value of A_{CL}, when a beacon is located on the top ceiling of pipe. Hence, by anchoring positions of beacons on the top of pipes, it is possible to calculate the depth of the water if we know the value of A_{CL} of the pipe. Also,the value of A_{CL} and $\alpha_{(a,\sigma)}$ are depending on the radius (a) and conductivity (σ) of the concrete pipe and these values are empirically derived from multiple experiments [11].

We want to find the distance A for SewerSnort localization as illustrated in Fig. 7. Knowing the radius of a pipe (R), we need to find d_1, d_2, and B to calculate A. Also, as explained in section 4, bank suction may drift a SewerSnort to the wall of pipeline. Thus, we assume $d_1 = 0$; i.e., $\frac{(d_2-d_1)}{2} = \frac{d_2}{2}$. Then, the current flow level ($2R - B$) can be estimated, when the drifter passes by the beacon, which can be detected by tracking the changes of RSSI (i.e., maximum point); i.e., $B = R + \sqrt{R^2 - \left(\frac{d_2}{2}\right)^2}$. The distance A can be estimated as: $A = \sqrt{\left(d^2 - \left(\frac{d_2}{2}\right)^2\right) - B^2}$.

4.3.2. De-noising RSSI samples

A de-noising process must be done beforehand to apply the channel model in a real world. Although destructive/constructive reflections have a small impact on measured RSSI values when there exists a dominant LOS [19], they cause rapid fluctuation. To de-noise the raw RSSI data we choose to use the Empirical Mode Decomposition (EMD) [12]. The EMD effectively filters out noise from the non-stationary time series signals such as RSSI data in SewerSnort.

[6] Numerous techniques for low-power medium access control exist and could be leveraged to reduce battery drain. These include supplemental "wake-up" RF circuitry [30] and low-power ultra-low drift clocking systems [36] to support extremely low duty-cycle time-division protocols [35].

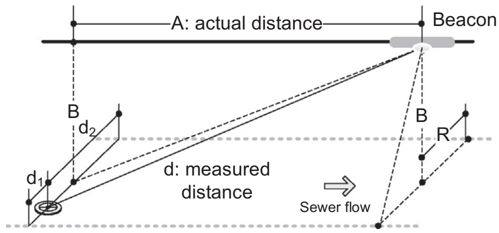


Fig. 7. Distance estimation in sewers.

Briefly, EMD is a data-driven signal processing technique. EMD decomposes signals into n empirical modes first and produces the residue which is the mean trend or constants. EMD algorithm is comprised of successive steps as follows:

(1) Identify all local maxima and local minima.
(2) Connect all local maxima using a cubic spline line as an upper envelope.
(3) Repeat step (2) for all local minima as a lower envelope.
(4) Compute the mean as $m(t) = \frac{E_{max}(t)+E_{min}(t)}{2}$.
(5) Extract the local detail h_1 as $h(t)_1 = X(t) - m(t)$ where $X(t)$ is a RSSI data at time t.
(6) Repeat steps 1–5 by treating the local detail h_i from the previous sifting as the raw data until $h(t)_m = h(t)_{m-1} - m(t)_m$. For example, h_1, the detail obtained after the first sifting, becomes data for the second sifting as $h(t)_2 = h(t)_1 - m(t)_2$.
(7) Then, the intrinsic mode function component of the data becomes $C(t) = h(t)_m$. $C(t)$ is a de-noised signal at time t.

4.3.3. Enhancement of location estimation assisted by flow velocity

The location of a drifter can be estimated using Eq. (3) and the de-noised RSSI data. However, the dynamic nature of signal propagation inside the pipe under mobile environments can influence the accuracy of de-noised RSSI data as we have seen in our experiments (Section 5). Under this circumstance, such a direct mapping can produce abrupt jumps and reverse of directions which results in high errors. Knowing that the sewer flow is laminar and exhibits spatio-temporal coherence as illustrated in the feasibility analysis section, abrupt changes of drifter proximity are not likely to happen in practice. On the basis of such characteristics, we propose to utilize the flow velocity in addition to Eq. (3) and the de-noised RSSI data to improve the accuracy. Also, we exploit the fact that the RSSI values peak right below beacon nodes and manhole's locations are known. Thus, whenever a peak is detected, localization error can be corrected, and location estimation restarts from the beacon node's location.

A drifter's location estimates can be improved using flow velocity as follows. For a given beacon node, we first de-noise the measured RSSI samples. From de-noise data, we find the peak and use the beacon's location as a departure position. Assuming that the drifter has travelled at a constant velocity V, we substitute the distance d in Eq. (3) with Vt where t is time, i.e., $RSSI(Vt)_{rx} = P_{tx} - \alpha_{(a,\sigma)} \times Vt - A_{CL}$. Recall that all the variables in Eq. (3) except the velocity V are known. Thus, we can find the velocity V that minimizes the sum of square errors between the modified model and the de-noised RSSI data.

In the event that a drifter has received RF signals from two adjacent beacon nodes while drifting (denoted as A and B), we have two different velocity estimates (V_A: moving away from A, and V_B: approaching to B). Since error is minimized right below a beacon node, both speeds are used to estimate locations as follows: from A, V_A is used for t_A unit times (A to B), and from B, V_B is used for t_B unit times (B to A). Say the distance between A and B is d_{AB} and drifting duration is t_{AB}, then, the following conditions must be satisfied to properly align estimated location from both directions: (1) $V_A t_A + V_B t_B = d_{AB}$ and (2) $t_A + t_B = t_{AB}$. Hence, we have $t_A = \frac{d_{AB} - v_A t_{AB}}{V_B - V_A}$, and $t_B = \frac{v_B t_{AB} - d_{AB}}{V_B - V_A}$. However, note that there is a sudden speed change in this scheme (say after t_A unit times).

For a given pipe, parameters in Eq. (3) such as $\alpha_{(a,\sigma)}$ and A_{CL} are affected by the changes of water depth. Calibrating these model parameters under a set of different water depths is greatly laborious task when there is a sewer flow. An alternative is to estimate the average speed between two beacon nodes, namely d_{AB}/t_{AB}. In this case, there is no sudden change of speed within a pipe segment formed by these consecutive beacons (e.g., A and B), yet can result in higher errors compared to the previous approach. Nonetheless, this approach can be very useful for handling the case when the distance between two consecutive manholes is too far to receive beacon messages or an intermediate beacon fails.[7]

4.4. Data acquisition

The acquired data can be packed and stored onboard all the way through the journey and collected after it is retracted. Even though the amount of data, with high sampling frequency, will grow rapidly, the required storage can be reduced significantly by compressing and storing the difference from the previous value.

First, we summarize the approximate storage requirements for the acquired data before the compression as listed in Table 2. Then, we can compress data by taking their characteristics into account.

Since, the sensor measurements are collected totally asynchronously from the beacon sensing, we account the storage requirement as:

$$Storage = (2bytes * f) + (7bytes * I), \tag{4}$$

where f is sampling frequency and I is beacon interval. For example, if $f = 1$ sample/500 ms[8] and $I = 1$ beacon/1 s,

[7] In practice, we do not anticipate an extended unreachable distance, because the average distance between sewer manholes is 71.93m [27] and the transmission range of 802.15.4 radio is 30m indoor and 70m outdoor [51].

[8] In general, the sewer flow velocity is approximately 0.2–1 m/s. Thus, the sampling frequency of 500 ms provides a reading for every 10–50 cm, and this is sufficient for "Meter" type accuracy. Since factual traveling path of SewerSnort may unprecedented, this velocity does not account for the nonlinear traveling path of SewerSnort.

Table 2
The approximate storage requirements.

Type	Data size (byte)
H_2S gas	2
Total (sample data)	2
GeoTag	2
Timestamp	4
Signal strength (RSSIval)	1
Total (beacon)	7

Fig. 9. Images of manhole cover.

we collect 39,600 bytes/h = 14,400 (sampling) bytes/h + 25,200 (beacon message) bytes/h. In general, 24 h is sufficient for a drifter to travel from upstream to a wastewater treatment plant [42]. Thus, a drifter may collect up to 1 MB for the entire trip. However, the required storage can be reduced significantly by compressing data and storing a difference from the previous value.

For example, considering the fact that the range of H_2S gas real-world sample data is no greater than 100 ppm and the environment does not change drastically from one region to the right next [4], we can use delta-compression. Since delta between two consecutive samples can be stored in one byte, we can truncate meaningless leading 8 bits without loss of information. Thus, we can reduce the storage requirements for sample data by half. Also, a beacon message can be extensively compressed by considering the fact that GeoTag is sequential and timestamp has small delta between adjacent timestamps. Thus, we can truncate leading 8 bits from a delta of GeoTag and leading 24 bits from a delta of timestamp without losing data. Consequently, a beacon message can be compressed into 3 bytes. After compressed the data, we have 18,000 bytes/h=7200 (sampling) bytes/h + 10,800 (beacon message) bytes/h and 432 KB in 24 h.

Although, a drifter can carry all acquired data to the destination, we may upload a portion of data to a base station for an emergency. When a drifter uploads data, the energy cost can be estimated as:

$$E_{total} = E_{tx} * (Mbits + Headers), \tag{5}$$

where E_{tx} is energy required to transmit one bit, and M is total bits to be uploaded. For example, if 2 KB (payload 2048 $*$ 8 bits + UDP Header 64 bits + IP Header 160 bits + 802.15.4 header 112 bits) are uploaded, we would deplete approximately 76.5 mAs and free 2048 bytes in flash memory assuming that there is no retransmission and we spend 5 mJ/bit to upload while 1 μJ/byte to read/write flash memory using IEEE 802.15.4 and MICAz flash memory [51]. Depending on the urgency and on the amount of data to be uploaded, we may equip a drifter with additional batteries.

4.5. Emergency notification

Wastewater collection systems are buried underground and they are not noticeable until a system failure occurs. Although most of system failures are caused by aging infrastructure, malicious attacks such as terrorism or sabotage can result catastrophic disaster. The disastrous series of sewer gas explosions in Guadalajara, Mexico on Wednesday, April 22, 1992, which caused death of 206 people and left almost unrecoverable damages to the city [44], demonstrates the potential impact of terrorist attack using underground sewer lines.

To deliver prompt alarms in case of emergency spills, fraudulent dumps, or astronomical explosive gas concentration, SewerSnort may upload collected data to base stations on a street level while traversing WCS before it reaches to the destination. As illustrated in Fig. 8, urgent

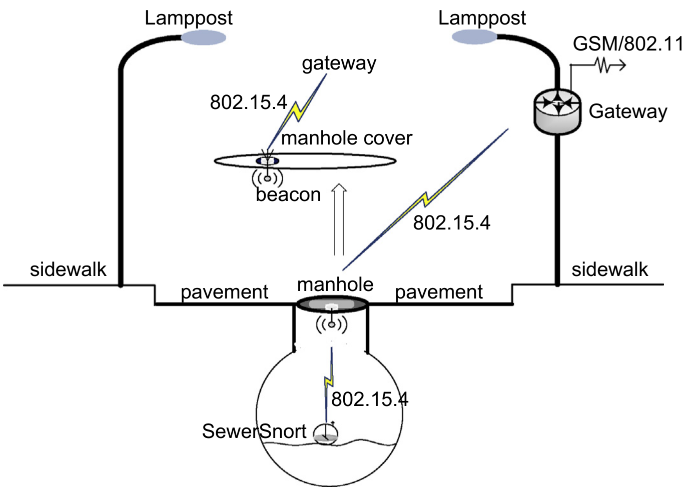


Fig. 8. Illustration of gateway/base station.

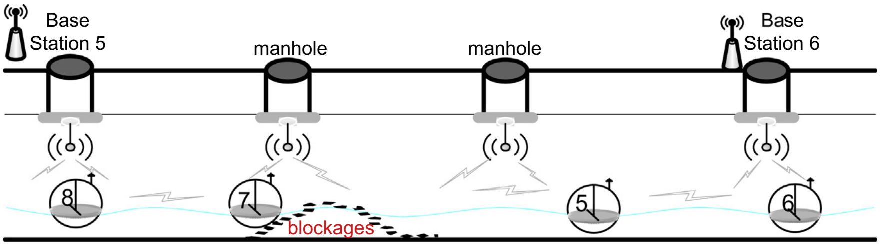


Fig. 10. Illustration of fault recovery.

data can be transmitted to a beacon node installed under a manhole cover. Then, the beacon node can relay the received data to a gateway node deployed on a nearby lamppost which will eventually deliver the data to a central node (to make a decision and take an action on it).

For wireless communications, ZigBee can be used between a beacon and a gateway if the distance is within the radio range of ZigBee. Alternatively, Wi–Fi can be used if the distance is not within the ZigBee radio range. Finally, a gateway node can transmit data to the central office either via wireless access networks such as 2/3G or wired access networks such as Digital Subscriber Line (DSL) and Passive Optical Network (PON).

Although severe signal attenuation between a beacon node and a gateway is encountered since the beacon node is located below ground (i.e., beneath the thick metal manhole cover as shown in Fig. 9); therefore, it makes the data communication challenging, a number of schemes has been designed and developed in an effort to address this transmission challenge. One solutions is employing the techniques used to enable wireless underground sensor networks where the sensor nodes buried underground can report sensor data to nodes on the surface wirelessly [14]. The other alternative is using an external antenna (over the surface) from the underground beacon node. We install external antennas on the surface of manhole covers to transmit data from underground to aboveground. However, the external antennas (or surface nodes) can be easily destroyed because manholes are typically located on human accessible roads and antennas can be run over by vehicles/pedestrians or be scrapped with snow plows.

In order to handle this problem, we can leverage the following two approaches proposed in the recent studies. Mastarone et al. [23] proposed to install a thin slot antenna into a conventional cast-iron manhole cover (by milling the manhole cover and placing a coaxial RF connector in the hole). However, this approach cannot fully protect an antenna from the harsh environment of the active roadbed and the continuous feeding of wire erosion. Thus, Jeong et al. [16] built a noble composite manhole cover with fiberglass fabric below which a thin slot antenna is attached to isolate from the external physical environment yet to efficiently radiate electromagnetic waves.

4.6. Fault recovery

Since a drifter is carried by sewer flow and has no control on its movements, it is unable to move around an obstacle when it gets stuck in blockage. To rescue a stranded drifter it is necessary to estimate its position. We can utilize base stations as follows. Each base station keeps a log of the periodic message exchanges heard from drifters that pass by. By analyzing the logs, we can find the section where the stranded drifter resides. As illustrated in Fig 10, base station 5 heard drifter 7, but base station 6 did not; drifter 7 is stuck between base station 5 and base station 6. For a more precise estimate, if we deploy a "convoy" of drifters that can hear and log each other probing messages, we can more precisely determine the location of the lost drifter. Upon retracting the surviving drifters at the end of the journey, we can estimate from their logs how many drifters are lost and can compute their approximate lost positions.

5. Experiments

We validate the end-to-end capability of our custom H_2S sensor board by comparing it with that of QRAE PLUS Multi-Gas Monitor. QRAE is an off-the-shelf gas monitor that is equipped with the same type of RAE H_2S electrochemical sensor element. Mounting our sensor system atop an Amigobot, a commercial mobile robot, and using it to mimic the sewer's flow rate, we evaluate the overall system performance.

5.1. SewerSnort gas sensor board evaluation

Industrial grade electrochemical sensor data acquisition modules cost in the thousands of dollars (far outside viability for SewerSnort). It is then incumbent to demonstrate that our low-power low-cost alternative (Fig. 6) performs sufficiently well. Sensing fidelity is fundamentally limited by the electrochemical element itself. For our chosen element [32], the maximum sensitivity[9] to H_2S is 0.75 $\frac{\mu A}{ppm}$, yet internal fluctuations and variations over temperature, limit accuracy to $\pm\frac{1}{2}$ ppm. We chose a value of 4.7 Ω for the transconductance element R_3 (Fig. 5) and a gain of 1000 ($R_4 = R_3 \times gain$) as it minimizes offset and Johnson thermal noise, while still resolving 0.5*ppm* H_2S changes into an output signal above the quantization threshold of the 10-bit ratiometric Analog-to-Digital Converter (ADC) in our chosen low-cost low-power processing node (a Crossbow

[9] In this context, Parts Per Million (ppm) denotes the number of particles of a desired gas per one million particles of the background gas or gases.

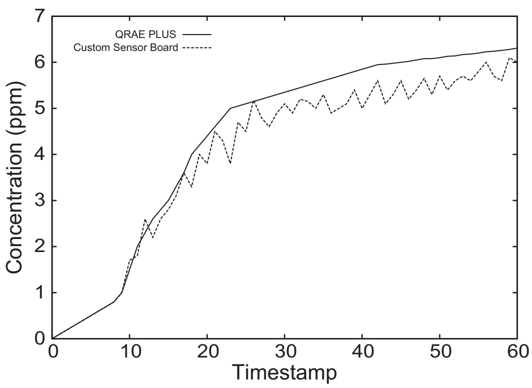


Fig. 11. Measured gas concentration using the QRAE industrial gas monitor and our SewerSnort AFE. The results agree almost exactly given that the sensor element uncertainty is ±0.5 ppm.

MicaZ). The transfer function for a 1 ppm signal (0.75 μA) follows:

$$\frac{\text{mV}}{\text{ppm}} = 0.75\frac{\mu\text{A}}{\text{ppm}}R_3\frac{R_4}{R_3} \approx 3.5\frac{\text{mV}}{\text{ppm}}. \quad (6)$$

For evaluation, we placed the QRAE and SewerSnort monitors in an airtight container and introduced a 10 ppm H_2S gas via a sealed injection tube. Fig. 11 presents the measured gas concentration in ppm. The figure shows that the measurement results from our AFE are within 0.5 ppm of the QRAE on average – e.g. below the sensor element's internal uncertainty. Since the experiments was performed on only H_2S gas, the sensor's selectivity was not analyzed at this time.

5.2. SewerSnort evaluation in a mobile environment

The SewerSnort gas board is interfaced with the MicaZ mote. Since the MicaZ mode has a 2.4 GHz IEEE 802.15.4 compatible radio, we also use it as a beacon node. We develop a TinyOS driver for the SewerSnort gas sensor board. The driver stores the following information in its flash memory: the gas measurements, the beacon messages that include the position of a beacon node, and the received signal strength of the beacon messages.

In the experiments, we first tried to derive the values of A_{CL} and $\alpha_{(a,\sigma)}$ in Eq. (3) for 10m concrete pipes with diameters of 1.5 m and 1.8 m. In order to estimate A_{CL} and $\alpha_{(a,\sigma)}$ for each pipe, we used a robust linear algorithm in Matlab. We place a beacon at the end of the pipes, and measure the RSSI values from 0 m to 10 m, incrementing the measure point by 0.5 m. Each measure collects 20 RSSIs, where every RSSI is averaged over a set of 500 samples. Thus, every measure requires 10,000 samples. We configure the beacon to send out a beacon packet every 10 ms, at the highest transmission power of the MicaZ. Figs. 14 and 15 show results of linear regression using Eq. (3).

After obtaining A_{CL} and $\alpha_{(a,\sigma)}$ for Eq. (3), we consider the mobility scenario of the SewerSnort drifter. We mimic the mobility of a SewerSnort drifter by using an Amigobot

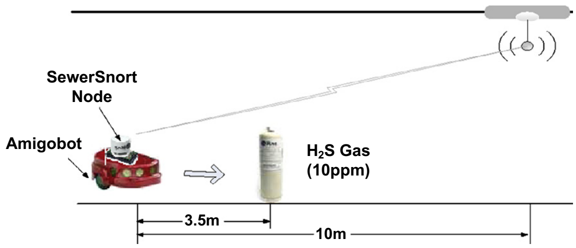


Fig. 12. Experiment scenario.

robot, a programmable, wirelessly controllable mobile robot. The SewerSnort node is placed on top of the Amigobot. We program the Amigobot to move from one end to the other with a constant speed of 1 m/s in a straight line. A H_2S gas cylinder (10 ppm) is placed 3.5 m away from the starting point. The overall scenario is summarized in Fig. 12. In our experiment, mainly the sensor's sensitivity was examined and there was no effect of wind or ventilation. In the future, we plan to include chimney effect by incorporating wind or ventilation to lab experiment scenarios.

Fig. 13 shows that the measured gas concentration starts rapidly increasing around the 3.4 m and then drastically decreasing after the 3.7 m. This range includes the position where we place the gas cylinder. The reason why we observe lower concentration than 10 ppm is due to gas diffusion in the air. A spike located at around 2.5 m in 1.5 m pipe is due to randomness of the gas diffusion.

For localization, we apply the EMD algorithm to denoise the RSSI measurement data in Figs. 16 and 17. We identify all local maxima $X_{max}(t)$ as $X(t-1) < X_{max}(t) > X(t+1)$ and all local minima $X_{min}(t)$ as $X(t-1) > X_{min}(t) < X(t+1)$ where $X(t)$ is RSSI value at time t. We then use cubic Bezier curves and Bernstein polynomials to connect all local maxima and all local minima for the upper envelope and for the lower envelop respectively as follows: $E(x) = \sum_{i=1}^{n}\binom{3}{i}X_i(1-t)^{3-i}t^i$. After the 4th iteration of

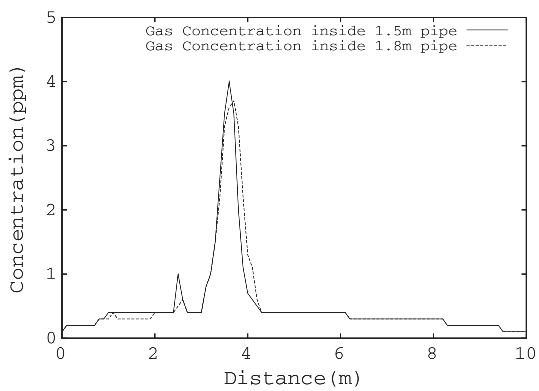


Fig. 13. Measured H_2S gas concentration (ppm) in 1.5 m, 1.8 m pipes.

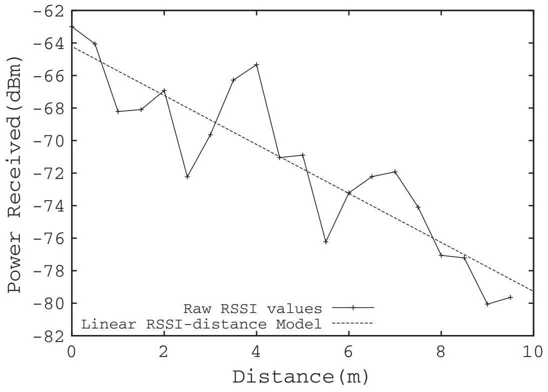


Fig. 14. Average received power results for 1.5 m pipe.

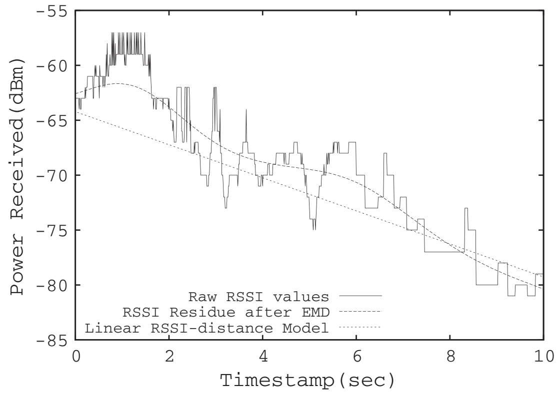


Fig. 16. Comparison with measured RSSI, EMD filtered RSSI, and linear RSSI-distance model (1.5 m pipe).

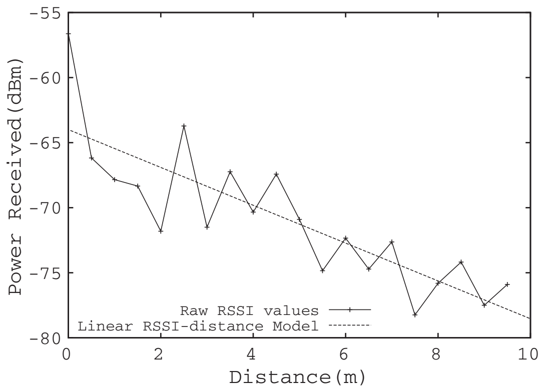


Fig. 15. Average received power results for 1.8 m pipe.

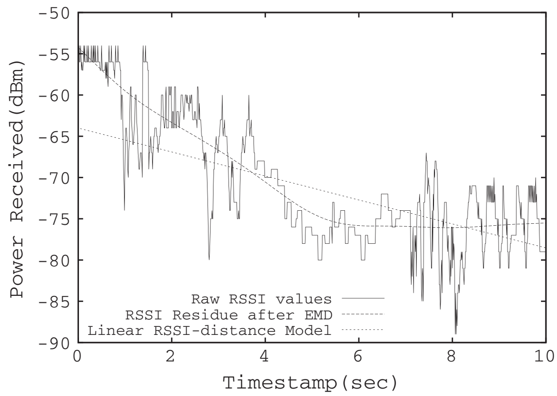


Fig. 17. Comparison with measured RSSI, EMD filtered RSSI, and linear RSSI-distance model (1.8 m pipe).

sifting, we reach the termination condition. Figs. 16 and 17 show the final residue after de-noising.

Eq. (3) can be directly used to estimate distance using measured RSSI data. As shown in the figures, however, the resulting distance estimates over time tends to fluctuate and may have abrupt jumps and reverse of directions, resulting in higher errors. For better location estimation, we exploit the fact that a flow velocity is relatively steady within a short pipe segment. Assuming that SewerSnort is drifting along the pipe at a constant speed V, we substitute d in Eq. (3) with Vt. This allows us to search for the drifter speed V that minimizes the errors from the smoothed RSSI values. In Figs. 16 and 17, we plot measured RSSI values, EMD filtered RSSI values, and our linear model with speed V that minimizes errors. The results show that the estimated speed is very close to the experiment scenario (less than 5% error). This meter-level accuracy may be sufficient for most sewer gas monitoring scenarios. If an application requires more accuracy, we need additional devices such as an inertial navigation device and a probabilistic localization model, which is part of our future work.

6. Related work

Wireless sensor networks have been widely utilized in various environmental monitoring systems. Among the wealth of research contributions, this section reviews only the few that are most significantly related to SewerSnort.

6.1. Advanced pipeline monitoring systems

Mobile robots can perform sewer inspection (e.g., anomaly detection) by autonomously navigating a pipeline. They are typically equipped with lights and cameras for pipeline profiling, and various sensors (e.g., sonar, infrared, laser) for autonomous navigation. To name a few prototypes, there are KURT developed by Kirchner et al. [18] and KANTARO by Ahrary et al. [1]. Mobile robot research in sewers has been focused on localization using an internal map and feature detection (e.g., manholes and inlets). Teichgräber et al. [41] proposed SEK, a “cable-guided” floating inspection tool that conducts camera inspections, recording major abnormalities such as erosion, deposits, obstacles and leaks in the gas space. SEK differs from SewerSnort in that (1) SewerSnort is an "unteathered" lightweight drifter that monitors in-sewer gases, and (2) SewerSnort performs localization using the beacons installed beneath sewer manholes.

Wireless sensor networks have recently employed in sewer monitoring [39,15]. PipeNet [39] uses a network of fixed wireless sensors to detect and locate leaks in the "full flowing" water transmission pipeline. The system collects pressure, flow velocity, and acoustic/vibration data at the fixed points along the pipelines. Then, an analytic algorithm is applied to detect and to locate the leaks. The IDEAS laboratory in Purdue university used a wireless sensor network for developing a system to prevent Combined Sewer Overflow (CSO) in South Bend, IN [15]. The system transmits an alert alarm through a wireless channel to facilitate automatic flow diversion when the flow level reaches the threshold.

6.2. Mobile robot localization in sewers

Mobile robot localization may be classified as relative, absolute, or a mixture of both. Relative localization uses internal sensors to estimate its current location such as odometry using internal sensors and dead reckoning using gyroscopes and compasses. As the robot moves, its actual position may deviate due to the accumulation of errors (e.g., wheel slippage). Thus, periodic absolute localization is crucial to long-term performance. Absolute localization requires either active beacons that transmit signals with position information (e.g., GPS), or known landmarks recognizable by the robot. The most popular approach is relative localization with landmark recognition. In sewers, there are only a few local features such as manholes, junctions, pipe joints and inlets that can be used as landmarks for localization [24]. Unfortunately, landmark detection in sewers experiences uncertainty with regard to detection and identity. Bayesian models are typically used to solve this problem using the conditional probability of the estimated location with respect to the observation and to the a priori probability distribution. Popular Bayesian methods include Kalman filtering [25], Markov [9], and Particle filtering (or Monte Carlo localization) [8]. A SewerSnort drifter localizes itself using active 802.15.4 beacons installed in sewer manholes. We are currently exploring augmenting the drifter with an inertial navigation sensor suite based on the works of [47]; and the Hidden Markov model (used in speech reorganization) will be used to find the trajectory that minimizes the error [20].

7. Conclusion and future work

This paper has presented an innovative sewer gas monitoring system based on a floating, drifting embedded sensor platform, the SewerSnort. We discussed the feasibility of a mobile drifting sensor by analyzing the sewer flow statistics and present the potential applications of in-sewer gas monitoring. Then, we designed an "inner-tube" shaped hull to handle the lateral force that pushes the drifter to the side of the sewers, presented the first single-supply differential ratiometric data acquisition architecture that targets electrochemical sensors for WCS monitoring applications, and proposed a Received Signal Strength Indicator (RSSI) based localization scheme for SewerSnort. Experiments based on a dry land robotic emulator have demonstrated the feasibility of the system, with extremely accurate gas readings aboard the float and adequate location estimates (errors within 5% over hundreds of meters).

The preliminary results are encouraging and will stimulate further research in the field. First, we will develop new applications sensors (or augment existing approaches) using drifting sensors such as pipe maintenance, flow characteristics monitoring, leak detection, exceptional dump monitoring, and sewer surveillance. For instance, preventive metal pipe maintenance will be assisted by the comparison of historical gas readings with typical pipe decay. Second, these applications may require a convoy of drifters deployed for better coverage (time/space), and enabling wireless communications among drifters will be very useful for adaptive sensing, localization, and near real-time data reporting. We will analyze communication patterns/requirements and develop efficient networking protocols for sewer drifter networks. Third, we will develop a realistic mobility model for drifters in sewer pipes, which will allow us to better understand sensor coverage and networking protocol performance (e.g., network connectivity and packet delivery ratio), especially when a convoy of sensors is deployed. Finally, we will study the trade-offs between localization accuracy and beacon deployments – the more the number of beacons, the better the accuracy.

Acknowledgements

We thank RAE Systems for providing a QRAE gas detector and H_2S electrochemical sensors (RAE 032-0102-000). We thank Woonghee Lee for providing 3D SewerSnort schematic. We appreciate the courtesy of Mr. Cowden, CEO of Rialto Concrete Pipe company, who provided us the experimental environment. This work is supported in part by the National Science Foundation under Grant No. 0722046.

References

[1] A. Ahrary, L. Tian, S. ichiro Kamata, M. Ishikawa, Navigation of an autonomous sewer inspection robot based on stereo camera images and laser scanner data, International Journal on Artificial Intelligence Tools 16 (5) (2008) 611–625.
[2] Cleveland Hopkins Airport Fumes Worry Workers, Remain Mystery. <http://archives.californiaaviation.org/airport/msg16476.html>.
[3] P. Bahl, V. Padmanabhan, RADAR: an in-building RF-based user location and tracking system, in: INFOCOM'00, Tel-Aviv, Israel, March 2000.
[4] P. Churchill, D. Elmer, Hydrogen sulfide odor control in wastewater collection systems, NEWEA Journal 33 (1) (1999) 57.
[5] C.-Y. Fan, R. Field, F. Hsiung Lai, Sewer-sediment control: overview of an EPA wet-weather flow research program, Technical Report EPA-600-J-03-188, US-EPA, National Risk Management Laboratory, Water Supply and Water Resource Division, Urban Watershed Management Branch, Edison, NJ, USA, 2006.
[6] R. Fenner, Approaches to sewer maintenance: a review, Urban Water 2 (42) (2000) 343–356.

[7] M.W. Fincham, Big boats, narrow channels, Chesapeake Quarterly Online 4 (2) (2005).
[8] D. Fox, W. Burgard, F. Dellaert, S. Thrun, Monte Carlo localization: efficient position estimation for mobile robots, in: National Conference on Artificial Intelligence, Orlando, FL, 1999.
[9] D. Fox, W. Burgard, S. Thrun, Markov localization for mobile robots in dynamic environments, Journal of Artificial Intelligence Research 11 (1999) 391–427.
[10] A. Guisasola, D. de Haas, J. Keller, Z. Yuan, Methane formation in sewer systems, Water Research 42 (6–7) (2008) 1421–1430.
[11] I. Howitt, J. Khan, S. Khan, Lumped parameter radio wave propagation model for storm drain pipe, in: Proceedings of First International Conference on Computer, Control and Communications, Karachi, Pakistan, 2007.
[12] N.E. Huang, Z. Shen, S.R. Long, M.C. Wu, H.H. Shih, Q. Zheng, N.-C. Yen, C.C. Tung, The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis, Royal Society of London Proceedings Series A 454 (1971) (1998) 903.
[13] T. Hvitved-Jacobsen, Sewer Processes: Microbial and Chemical Process Engineering of Sewer Networks, CRC, 2001.
[14] E.P. Ian, F. Akyildiz, Wireless underground sensor networks: research challenges, Ad Hoc Networks 4 (2006) (2006) 669–686.
[15] Purdue University: IDEAS Mirowave Laboratory. <http://engineering.purdue.edu/IDEAS/Enviro.html/>.
[16] S. Jeong, C. Yang, J. Courter, S. Kim, B. Pipes, W. Chappell, Multilayer composite for below ground embedded sensor networking, in: IEEE International Conference of Antennas and Propagation, 2008.
[17] J. Kim, J. Lim, J. Friedman, U. Lee, L. Vieira, D. Rosso, M. Gerla, M. Srivastava, SewerSnort: A drifting sensor for in-situ sewer gas monitoring, in: IEEE SECON'09, Rome, Italy, 2009.
[18] F. Kirchner, J. Hertzberg, A prototype study of an autonomous robot platform for sewerage system maintenance, Autonomous Robots 4 (4) (1997) 319–331.
[19] E. Kjeldsen, M. Hopkins, An experimental look at RF propagation in narrow tunnels, in: MILCOM'06, Washington, DC, 2006.
[20] J. Krumm, E. Horvitz, LOCADIO: inferring motion and location from Wi–Fi signal strengths, in: Mobiquitous'04, Boston, MA, 2004.
[21] K. Lorincz, M. Welsh, MoteTrack: a robust, decentralized approach to RF-based location tracking, in: LoCA'05, Munich, Germany, 2005.
[22] Datasheet, MCP6041: 600nA, Rail-to-Rail Input/Output Op Amps, Microchip Corporation, 2002.
[23] J. Mastarone, W. Chappell, Urban sensor networking using thick slots in manhole covers, in: IEEE Antennas and Propagation Society International Symposium, 2006.
[24] A. Nassiraei, Y. Kawamura, A. Ahrary, Y. Mikuriya, K. Ishii, A new approach to the sewer pipe inspection: fully autonomous mobile robot "KANTARO", in: IECON 2006, Paris, 2006.
[25] R. Negenborn, Robot localization and Kalman filters, Technical Report INF/SCR-0309, Utrecht University, 2003.
[26] Inventory of New York City GREENHOUSE GAS EMISSIONS. <http://www.nyc.gov/html/om/pdf/ccp_report041007.pdf>.
[27] A.S. of Civil Engineers, Protocols for identifying sanitary sewer overflows, Technical Report CX 82697-01-0, USEPA, 2000.
[28] L.A.D. of Public Works Bureau of Sanitation, Year at a glance 2008–2009, City of Los Angeles, Department of Public Works, Bureau of Sanitation, Technical Report YAG 2008-2009, City of Los Angeles, 2009.
[29] P. Pathirana, N. Bulusu, A. Savkin, S. Jha, Node localization using mobile robots in delay-tolerant sensor networks, IEEE Transactions on Mobile Computing 4 (3) (2005).
[30] N. Pletcher, J.M. Rabaey, Ultra-low power wake-up receivers for wireless sensor networks, PhD thesis, EECS Department, University of California, Berkeley, 2008.
[31] Connection Code Bulletin 2008-4, <http://www.powerwater.com.au/__data/assets/pdf_file/0016/6235/bulletin_2008_4_CCTV_sewer_inspection_requirement.pdf>.
[32] Datasheet, Electrochemical H^2S Sensor 032-0102-000, RAE Systems.
[33] D.M. Revitt, J.B. Ellis, N. Paterakis, Comparison of tracer techniques for monitoring sewer losses, Journal of Environmental Monitoring 8 (5) (2006) 564–571.
[34] D. Rosso, M.K. Stenstrom, The carbon-sequestration potential of municipal wastewater treatment, Chemosphere 70 (8) (2008) 1468–1475.
[35] T. Schmid, J. Friedman, Z.M. Charbiwala, Y.H. Cho, M.B. Srivastava, Low-power high-accuracy timing systems for efficient duty cycling, in: ISLPED'08, Bangalore, India, August 2008.
[36] T. Schmid, J. Friedman, Z.M. Charbiwala, Y.H. Cho, M.B. Srivastava. XCXO: an ultra-low cost ultra-high accuracy clock system for wireless sensor networks in harsh remote outdoor environments, in: ISSCC/DAC'08, San Francisco, CA, 2008.
[37] Sewer Design Manual – Part F, <http://www.eng.lacity.org/techdocs/sewer-ma/index.htm>.
[38] A.U. Spencer, S.S. Noland, L.J. Gottlieb, Bathtub fire: an extraordinary burn injury, Journal of Burn Care & Research 27 (1) (2006) 97–98.
[39] I. Stoianov, L. Nachman, S. Madden, PIPENET: a wireless sensor network for pipeline monitoring, in: IPSN'07, Cambridge, MA, 2007.
[40] Streetline City Infrastructure Technologies, <http://www.streetlinenetworks.com/site/index.php>.
[41] B. Teichgräber, J. Stemplewski, H. Althoff, N. Elkmann, Remote controlled inspection device for large sewers, Water Practice & Technology 1 (4) (2006).
[42] US-EPA, Guide for evaluating capacity, management, operation, and maintenance (CMOM) programs at sanitary sewer collection systems, Technical Report EPA-305-B-05-002, US-EPA Office of Enforcement and Compliance Assurance, 2005.
[43] US-EPA, Real time control of urban drainage networks, Technical Report EPA-600-R-06-120, US-EPA Office of Research and Development, 2006.
[44] P. Varley, Responding to disasters: the story of the guadalajara sewer explosion, Technical Report C16-94-1180.0 p3-6, Kennedy School of Government Case Program, 1994.
[45] J. Vollertsen, A.H. Nielsen, H.S. Jensen, T. Hvitved-Jacobsen, Modeling the formation and fate of odorous substances in collection systems, Water Environment Research 80 (2) (2008) 118–126.
[46] Wellcare Information for You about Turbidity in Drinking Water, <http://www.watersystemscouncil.org>.
[47] O.J. Woodmann, An introduction to inertial navigation, Technical Report TR-696, UCAM-CL, 2007.
[48] C. Yalamanchili, M.D. Smith, Acute hydrogen sulfide toxicity due to sewer gas exposure, The American Journal of Emergency Medicine 26 (4) (2006) 518.e5–518.e7.
[49] L. Zeindlhofer, Filling the sewer pipe – advanced FTTH deployment technologiess, in: FTTH Conference Expo'07, Orlando, FL, 2007.
[50] L. Zhang, P.D. Schryver, B.D. Gusseme, W.D. Muynck, N. Boon, W. Verstraete, Chemical and biological technologies for hydrogen sulfide emission control in sewer systems: a review, Water Research 42 (1-2) (2008) 1–12.
[51] Specification of ZigBee Technology, <http://www.ZigBee.org/>.

Jihyoung Kim received M.S. degree in computer science from University of California, Los Angeles, in 2009. He is currently working toward Ph.D. degree in computer science at University of California, Los Angeles (UCLA). His research interests include sensor networks, social networks, cloud computing and network security.

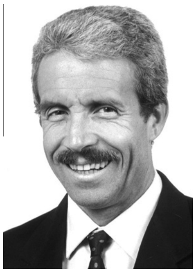
Jonathan Friedman has spent most of his professional career split between IT/MIS administrative duties and mixed-signal PCB design. He was the Director of Database Support Services for Sonic Associates (an IMAX company), Director of US Technological Cooperation Students at the Chernigov State Institute for Economics and Management (Chernigov, Ukraine, 2002), and is the Founder of HalcyonIT, an IT outsourcing firm for many small-to-medium size businesses. In his research at the Networked and Embedded Systems Laboratory, University of California, Los Angeles (UCLA), he is interested in improving the physical sensor layer of wireless mobile embedded sensor networks through more advanced implementations and designs. Specially, he is targeting the problem of location of a sensed entity by implementing a new architecture for robust (noise-immune), low-latency (many positional fixes per second), high-accuracy localization for mobile nodes. Additional interests lie in relaxing the deployment

constraints and requirements for static (nonmobile) beacons. Application areas of interest lie in entertainment. In collaboration with UCLA's School of Theater, Film, and Television, his work is being shaped and adapted to fit within the unique constraints of this application space.

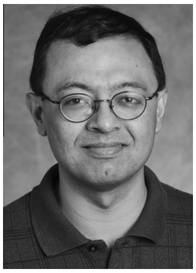
Uichin Lee is an assistant professor in the Department of Knowledge Service Engineering at Korea Advanced Institute of Science and Technology (KAIST). He received a B.S. in computer engineering from Chonbuk National University in 2001, an M.S. degree in computer science from KAIST in 2003, and a Ph.D. degree in computer science from the University of California at Los Angeles (UCLA) in 2008. Before joining KAIST, he was a member of technical staff at Bell Laboratories, Alcatel-Lucent until 2010. His research interests include distributed systems and mobile/pervasive computing.

Luiz F.M. Vieira is an Associate Professor at the Computer Science Department at the Federal University of Minas Gerais (UFMG), Belo Horizonte, Brazil. Dr. Vieira holds a Ph.D. in Computer Science from the University of California, Los Angeles (UCLA), 2009. His research areas are ad hoc and sensor networks, network coding, computer networks and distributed systems.

Diego Rosso is an Assistant Professor in the Civil and Environmental Engineering Department at the University of California, Irvine. During the past ten years he has studied wastewater treatment processes, energy conservation in treatment processes, and carbon footprint models. Since January 2008 he has been directing the UCI Environmental Processes Laboratory, leading a team of 12 student researchers focusing on carbon- and energy- footprint analyses and the water-energy nexus. Previously, he was at UCLA, where he received his Ph.D. in Environmental Engineering in 2005. He is also a Chemical Engineering Laureate from the University of Padua in Italy. He is an active member and campus adviser of Engineers Without Borders.



Mario Gerla is a Professor in the Computer Science at UCLA. He holds an Engineering degree from Politecnico di Milano, Italy and the Ph.D. degree from UCLA. He became IEEE Fellow in 2002. At UCLA, he was part of the team that developed the early ARPANET protocols under the guidance of Prof. Leonard Kleinrock. At Network Analysis Corporation, New York, from 1973 to 1976, he helped transfer ARPANET technology to Government and Commercial Networks. He joined the UCLA Faculty in 1976. At UCLA he has designed and implemented network protocols including ad hoc wireless clustering, multicast (ODMRP and CodeCast) and Internet transport (TCP Westwood). He has lead the $12M, 6 year ONR MINUTEMAN project, designing the next generation scalable airborne Internet for tactical and homeland defense scenarios. He is now leading two advanced wireless network projects under ARMY and IBM funding. His team is developing a Vehicular Testbed for safe navigation, urban sensing and intelligent transport. A parallel research activity explores personal communications for cooperative, networked medical monitoring (see http://www.cs.ucla.edu/NRL for recent publications).



Mani Srivastava is on the faculty at UCLA, where he is Professor and Vice Chair in the Electrical Engineering Department, with a joint appointment in the Computer Science Department. He is also associated with the NSF Center for Embedded Networked Sensing, and his research at CENS since the early days of Sensor Networking research has addressed multiple aspects of embedded, pervasive, and participatory sensing technologies and applications. His current research interests include: sensing and control technologies for energy management in smart buildings, smart grids, and computing/communication systems at multiple scales; mobile and wearable sensing for biomedical and psychosocial applications; underwater bio-mimetic sensing and communications; privacy and data quality in sensory information; and, emerging hardware-software platform technologies. Before joining UCLA, Mani received his BTech from IIT Kanpur, M.S. and Ph.D. from Berkeley, and worked in Networked Computing Research at Bell Laboratories for several years. He is a Fellow of the IEEE, and recently served as the Editor-in-Chief of the IEEE Transactions on Mobile Computing.