A Low-Cost Sensor Network for Real-Time Monitoring and Contamination Detection in Drinking Water Distribution Systems

Theofanis P. Lambrou, Christos C. Anastasiou, Christos G. Panayiotou, and Marios M. Polycarpou

Abstract—This paper presents a low cost and holistic approach to the water quality monitoring problem for drinking water distribution systems as well as for consumer sites. Our approach is based on the development of low cost sensor nodes for real time and in-pipe monitoring and assessment of water quality on the fly. The main sensor node consists of several in-pipe electrochemical and optical sensors and emphasis is given on low cost, light-weight implementation, and reliable long time operation. Such implementation is suitable for large scale deployments enabling a sensor network approach for providing spatiotemporally rich data to water consumers, water companies, and authorities. Extensive literature and market research are performed to identify low cost sensors that can reliably monitor several parameters, which can be used to infer the water quality. Based on selected parameters, a sensor array is developed along with several microsystems for analog signal conditioning, processing, logging, and remote presentation of data. Finally, algorithms for fusing online multisensor measurements at local level are developed to assess the water contamination risk. Experiments are performed to evaluate and validate these algorithms on intentional contamination events of various concentrations of escherichia coli bacteria and heavy metals (arsenic). Experimental results indicate that this inexpensive system is capable of detecting these high impact contaminants at fairly low concentrations. The results demonstrate that this system satisfies the online, in-pipe, low deployment-operation cost, and good detection accuracy criteria of an ideal early warning system.

Index Terms—Water quality monitoring, flat surface sensors, turbidity sensor, multi-sensor system, sensor networks, arsenic & bacteria contamination detection.

I. INTRODUCTION

LEAN drinking water is a critical resource, important for the health and well-being of all humans. Drinking water utilities are facing new challenges in their real-time operation because of limited water resources, intensive budget requirements, growing population, ageing infrastructure, increasingly stringent regulations and increased attention towards safeguarding water supplies from accidental or deliberate contamination. There is a need for better on-line water monitoring systems given that existing laboratory-based methods are too slow to develop operational response and do not provide a level of public health protection in real time. Rapid detection (and response) to instances of contamination is critical due to the potentially severe consequences to human health.

Traditional methods of water quality control involve the manual collection of water samples at various locations and at different times, followed by laboratory analytical techniques in order to characterize the water quality. Such approaches are no longer considered efficient [1]–[5]. Although, the current methodology allows a thorough analysis including chemical and biological agents, it has several drawbacks: a) the lack of real-time water quality information to enable critical decisions for public health protection (long time gaps between sampling and detection of contamination) b) poor spatiotemporal coverage (small number locations are sampled) c) it is labor intensive and has relatively high costs (labor, operation and equipment). Therefore, there is a clear need for continuous on-line water quality monitoring with efficient spatio-temporal resolution. US Environmental Protection Agency (USEPA) has carried out an extensive experimental evaluation [6] of water quality sensors to assess their performance on several contaminations. The main conclusion was that many of the chemical and biological contaminants used have an effect on many water parameters monitored including Turbidity (TU), Oxidation Reduction Potential (ORP), Electrical Conductivity (EC) and pH. Thus, it is feasible to monitor and infer the water quality by detecting changes in such parameters.

Given the absence of reliable, in-line, continuous and inexpensive sensors for monitoring all possible biological and chemical contaminants, our approach is to measure physico-chemical water parameters that can be reliably monitored with low cost sensors and develop low cost networked embedded systems (sensor nodes) as well as contamination detection algorithms to fuse these multi-sensor data in order to infer possible contamination events. Even though this approach may suffer from some false alarms, it can be compensated/eliminated by the large scale deployment and the possibility of correlating the decisions from various sensor nodes which is the topic of our future work.

There is a clear need for a shift in the current monitoring paradigm and this paper proposes the idea of monitoring...
the quality of water delivered to consumers, using low cost, low power and tiny in-pipe sensors. The main contribution of this paper is the design and development of a low cost system that can be used at the premises of consumers to continuously monitor qualitative water parameters and fuse multi-parametric sensor response in order to assess the water consumption risk. In particular, the contributions regarding the low cost system is the design and development of low cost networked embedded systems as well as optical sensors (turbidity) for water quality monitoring, the development of event detection algorithms using fusion techniques and the experimental evaluation and validation of system performance in various concentrations of microbiologically (E.coli) and chemically (Arsenic) contaminated drinking water.

The remaining of this paper is organized as follows. Section II reviews related work. Section III presents the methodology and justification for the selection of water quality parameters to be monitored. Section IV presents the system design and the experimental implementation of the hardware and software modules. Section V validates the performance of the developed system and finally the paper concludes with Section VI.

II. RELATED WORK

A preliminary version of this article has appeared in [2]. In this article, we present an improved hardware platform, develop a new advanced contamination event detection algorithm and provide an experimental evaluation and validation of system and event detection algorithms in the presence of real microbiological and chemical contamination events.

A limited number of on-line, reagent-free water monitoring systems are commercially available [7] (e.g. Hach HST GuardianBlue [8], J-MAR BioSentry [9], etc), but these systems are bulky (sensors are installed in flow cells located in cabinets) and remain cost prohibitive for large scale deployments (cost tens of thousands of dollars per unit). It is worth mentioning that cost is mostly attributed not to sensing probes but to instrumentation-automation controllers (analyzers) and panels. Such systems can take frequent samples of the water quality at a very limited number of locations. However, substantial proportion of contamination problems is attributable to problems within distribution systems and due to the limited spatio-temporal sampling, it is impossible for the water companies and consumers to know the quality of potable water delivered to consumer households.

A number of bare multi-parametric sensor arrays have been developed and presented in the literature based on various sensor technologies. A recent review on multi-parametric solid-state sensors for water quality is given [3]. A chemical sensor array for water quality monitoring based on thick-film technology is presented in [24], [25], [26], and [27], these sensors are very low cost, though they have limited lifetime (few months) and require a conventional glass reference electrode to operate accurately. Along similar lines, a multi-parametric sensor array based on semiconductor ruthenium oxide nanostructures is presented in [3] and [28].

In addition, several water monitoring microsystems (sensor nodes) have been developed for large scale water monitoring based on wireless sensor networks (WSNs) technology. In [29] a sensor node is developed for monitoring salinity in ground waters as well as the water temperature in surface waters. In [33] and [38], the authors have developed a WSN and an energy harvesting system (based on a solar panel) to monitor nitrate, ammonium and chloride levels in rivers and lakes. Energy harvesting techniques along with hibernation methods play an important role in extending the lifetime of sensor nodes. A survey on energy harvesting for WSNs is provided in [39] and [40]. Finally, in [34] an autonomous boat equipped with water sensors is proposed to collect samples from lakes using the A* search algorithm. More efficient navigation algorithms for a group of boats with obstacle avoidance are presented in [35]–[37].

Next, we provide a number of academic and commercial efforts aim to develop hardware and software platforms for real-time monitoring of the water distribution systems. In [41] a WSN is proposed to monitor hydraulic parameters in order to detect events such as leaks, pipe bursts. A cost effective multi-sensor probe (Endetec KAPTA 3000-AC4) for monitoring chlorine, conductivity and pressure without any event detection algorithms has been proposed by Endetec [42] in 2012. Finally, in [43] an optical interferometric sensor along with an event detection algorithm to monitor refractive index aberrations in water has been developed.

Apart from the on going research towards the design and development of sensors and microsystems another parallel research direction is that of the development of software and algorithms for the detection of water quality anomalies and contamination events. A thorough survey on recent advances in this area is provided in [30]. A limited number of event detection software is commercially available (Hach Event Monitor [8], BlueBox [10]). A currently freely available tool is CANARY software [11] developed at Sandia National Laboratories in collaboration with the USEPA. CANARY indicates possible contamination events by using a range of mathematical and statistical techniques to identify the onset of anomalous water quality incidents from online raw sensor data. Other event detection and data validation methodologies are given in [31] and references therein.

III. METHODS

Drinking water quality standards are determined according to World Health Organization (WHO) [12] guidelines for drinking-water quality as well as other pertinent organizations (i.e. EU [13], USEPA [14]). These organizations set the standards for drinking water quality parameters and indicate which microbiological, chemical and indicator parameters must be monitored and tested regularly in order to protect the health of the consumers and to make sure the water is wholesome and clean.

For the developed system, the selection of the physico-chemical parameters to be monitored was based on extensive scientific literature review [6], [16], [17], and [18] on the relation between certain physicochemical parameters and chemical or biological contaminations that present in water. Table I enumerates the suggested parameters to be monitored...
from high to low correlation significance when interpreting water contaminations (assess hazard). Table I also presents the measurement cost (for purchase and maintenance) associated with these parameters based on recent review [19] of measurement and instrumentation methods, compensation and calibration procedures and probe lifetime concerning these parameters. Therefore, the parameters selected to be monitored are the following: 1) Turbidity, 2) Oxidation Reduction Potential (instead of Free Chlorine), 3) Temperature, 4) pH, and 5) Electrical Conductivity.

It is noted that Free Chlorine concentration (HOCl) can be approximated based on the ORP, pH and temperature measurements. Free chlorine monitoring is expensive because it is very sensitive in the pH, temperature, flow and pressure of the sample. Therefore accurate free chlorine measurements require a flow cell with additional pH and temperature sensors for compensation. Nitrates, though considered as an important parameter for human health is not selected because measurement methods are subjected to failures (Ion-Selective electrodes) or are cost prohibitive (UV spectrophotometric method). In [15], a new promising method is presented based on a PCB planar electromagnetic sensor. Finally, dissolved oxygen is not selected due to several compensations and frequent membrane replacements needed.

Conventional combined electrodes (for ORP and pH) have been widely used due to their good sensitivity, selectivity, stability and long lifetime. However, conventional pH glass electrodes have several disadvantages due to the intrinsic nature of the glass membrane. For example, they have limited pressure tolerance, exhibit a sluggish response, require a high input impedance signal conditioning circuits and it is difficult to miniaturize based on current manufacturing technologies. Therefore, a number of emerging-alternative sensor technologies in various stages of research and development have been proposed in the literature.

Thick film chemical sensor arrays developments show that it is possible to develop a single miniaturized multi-parametric sensor probe in a cost effective manner, however thick film chemical sensors have limited lifetime (few months), suffer from electrode drift (due to salt loss) and the development of a stable reference electrode is not possible so far [25]. ISFET based microsensors (developed using MOSFET semiconductor technology) offer advantages such small size (mass fabrication and compact probes), robustness (no glass membranes), low output impedance and rapid response, however they have several limitations as they require a glass reference electrode (REFET) to operate robustly and encapsulation is difficult, which increases dramatically the final cost of the sensors [32]. Nano-sensors based on nanostructures of noble metals and their oxides (like Pt, Ru, Ir) is a recent promising concept however developments so far suffer from several drawbacks like temperature dependent delay response and non-deterministic potential drift (electrolysis of water on oxide surfaces and unpredictable temperature dependence) [28]. Therefore, despite the recent advances in sensor development technologies, the reliability and performance of conventional glass electrodes is still unsurpassed for continuous water quality monitoring [7]. Therefore, conventional (pH, ORP) glass electrodes and solid-state sensors (TU, EC, T) are used in this work as they provide the most reliable technology.

In-line water sensors illustrate the need for efficient and periodic probe cleaning to maintain reliable measurements. Cleaning mechanisms constitute an important cost parameter which can consume as high as 50% of the operational budgets. Conventionally, ultrasonic, brush, water-jet, or chemical type of automatic cleaners [20] are used to remove coatings from the sensor probes. Recently, several alternative cost effective methods have been proposed that can either actively remove fouling (e.g. electrolysis) or passively prevent fouling (copper mesh or CuO2 doped materials). In this work, flat measuring surface probe method [23] is used because is the most cost effective, passive self-cleaning method and is based on the mechanical package and design of the probe. When the electrode’s flat measuring surface is exposed to turbulent flow, the resulting scrubbing action provides a self-cleaning effect in most applications under medium range flows. The flat sensing surface virtually eliminates deposits that can foul the electrode and significantly reduces necessary maintenance. This simple, but effective method has no moving parts, requires no power and also prolongs electrode life and eliminates breakage. Additional antifouling technologies have been proposed for solid-state and optical sensors based on nano-scale materials possessing super-hydrophobic properties [21], [22].

### IV. Platform Design

#### A. System and Sensors Development and Integration

The overall system architecture under discussion in presented in Fig. 1 and is comprised of the following three subsystems: a central measurement node (PIC32 MCU based board) that collects water quality measurements from sensors, implements the algorithm to assess water quality and transmits data to other nodes, a control node (ARM/Linux based platform) that stores measurement data received from the central measurement node in a local database and provides gateway to the internet, visualize data (charts), and sends email/sms alerts and finally a tiny notification node(s) (PIC MCU based board) that receives information from the central measurement node through an interconnected ZigBee RF transceiver and provides local near-tap notifications to the user (water consumer) via several interfaced peripherals (LED, LCD, Buzzer).

It should be noted that the central measurement node serves as the sensor node. The idea is to install these sensor nodes
in many consumer sites in a spatially-distributed manner to form a WSN that will monitor the drinking water quality in the water distribution system from the source to the tap. The central measurement node is interfaced to multi-parameter sensor array comprised of Turbidity (TU), ORP, pH, Electrical Conductivity (EC) and Temperature (T) sensors. The in-pipe Turbidity sensor is constructed from scratch based on our previous work [1] while the other sensor probes obtained from SensoreX Corp®. The pH sensor embeds an RTD sensor which is used for temperature sensing and temperature compensation of pH and EC measurements. TU, ORP, pH and toroidal EC sensors have flat measuring surfaces for cost effective self-cleaning. The complete system photo, with TU, ORP, pH, EC and T sensors as well as a rotor-flow sensor mounted in a plastic pipe, is shown in Fig. 2.

**Turbidity Sensor Development:** Although there is plenty of turbidity measuring instruments available on the market at the moment, most of them are expensive and not directly compatible with in-pipe, in-line requirements as well as WSNs technology. Therefore, the goal is to develop a low cost, easy to use and accurate enough turbidity sensor for continuous in pipe turbidity monitoring in water distribution systems using commercial off-the self-components. The turbidity sensor development was based on the ratio turbidimeter design (see Fig. 3) where both transmitted and scattered light intensities are measured to eliminate errors (interferences) due to IR emitter intensity drift and sample absorption characteristics. An infrared (860nm) narrow beam LED emits light through an optical gap to the water sample and two IR photodiodes separated around 1cm from the emitter receive simultaneously the 90° scattered and 0° transmitted light. The photodiodes spectral sensitivity are selected to fit with that of the IR light source. The instrumentation and analog signal conditioning of the sensor is as follows: The IR emitter is pulsed at 1kHz with a square wave signal and the photodiodes convert the light directly into electrical current, then a high-gain, low-noise CMOS (Complementary metal-oxide-semiconductor) transimpedance amplifier with background light rejection is used to convert the each photocurrent to voltage output. The ac output of each transimpedance amplifier is then converted to a dc signal using a precision active peak detector. Finally the 90° scattered dc signal is further conditioned by an instrumentation amplifier for 0 NTU offset nulling and additional amplification. The conditioned voltage outputs are then sampled by a 10 bit A/D converter with reference voltage of 1.1V and the sensor output voltage $V = \frac{V_{90\degree}}{V_{0\degree}}$ is given as the signal ratio of the scattered $V_{90\degree}$ to the transmitted $V_{0\degree}$ voltage, $c$ is calibration coefficient.

An indirect method for the sensor calibration was employed, in order to avoid the use of the carcinogen and expensive chemical formazin solutions. Therefore, a number of samples were created and the turbidity of each sample is measured both by the turbidity sensor under calibration and by a laboratory turbidimeter (Lutron TU-2016) used as reference. Then the relationship between turbidity (in NTU) and the voltage output (in mV) of the turbidity sensor is extracted and given by $TU = 0.1035V - 0.292$. The sensor generates an output voltage proportional to the turbidity or suspended particles and has a linear response in the range of 0-100 NTU with 0.1 NTU resolution. Finally, as shown in Fig. 3 the turbidity sensor probe was mounted in a flat surface PTFE (teflon) housing and sealed in a hydraulic Tee fitting for inline installation.

Apart from TU sensor, analog signal conditioning circuits, calibration and compensation procedures were developed for pH, ORP, RTD and conductive/inductive EC sensors. Considerable attention is given to acquire linear response, reduce noise and attain high resolution and accuracy. A dedicated PIC based microsystem is developed for each parameter to
Fig. 4. The first stage of analog signal conditioning circuitry. (a) Turbidity preamplifier. (b) Conductivity preamplifier. (c) ORP preamplifier. (d) pH preamplifier. (e) Temp.

Fig. 5. Software platform.

accomplish this task. The first stage of analog signal conditioning circuitry for each parameter is presented in Fig. 4 while Table II shows the results regarding laboratory evaluation (using standard buffer solutions and reference instruments) of each parameter along with the quality range suggested by WHO guidelines and EU standards. The overall power consumption of the central measurement sensor node with the on board LEDs off and the RF Xbee transceiver module sending water quality data every 5s is about 50mA at 5V operating voltage, however further improvements are planned to minimize the power consumption using hibernation schemes.

It worth mentioning that wireless communication is by far the largest consumer of the energy of the sensor node, compared to other functions such as sensing and computation.

The components for the complete system prototype cost approximately €400 (€300 for sensors-mounts-enclosures and €100 for microsystems and electronic components) which is at least an order of magnitude less expensive than commercially available multi-parameter instruments. It worth mentioning that site preparation costs will be also minimized if such low cost and lightweight systems are deployed in consumer premises instead of buried main supply pipes.

The software platform developed for the control node is illustrated in Fig. 5. This platform enables real time measurement charts of monitored parameters, real time assessment of water quality and sensor calibration instructions through a Graphical User Interface (GUI). It also logs sensor data in a local database and posts data to web using Pachube open source web platform. Using Pachube scripts the user can setup various thresholds for sending notifications via sms or email. Fig. 6 illustrates the main window of the internet platform.

B. Contamination Event Detection Algorithms

Two event detection algorithms were developed to fuse on-line multi-sensor measurements in order to assess the water contamination risk when anomalies are detected. An event detection algorithm enables the system to act as an “early warning system” for possible potable water quality deterioration at the point of installation (e.g. homes). Both algorithms are based on normalized sensor outputs given by

\[ N_i = \frac{|S_i - \mu_i|}{\tau_i \sigma_i} \]

where \( S_i \) is the current measurement of parameter \( i \in \{TU, ORP, pH, EC\} \), \( \mu_i, \sigma_i \) are the mean and standard deviation over a moving time window \( w \) and \( \tau_i \) is a sensor based parameter associated with measurement accuracy of each parameter \( i \). Normalized sensor outputs \( N_i \) are used to filter baseline (i.e mean) fluctuations.

The objective of the event detection algorithms is to activate an alarm when normalized sensor outputs exhibit sudden and significant changes, given that these changes are bounded within the quality ranges suggested by drinking water quality standards (see Table II, quality range). The detection of water quality changes that are outside the expected quality ranges (min/max violations) is easier and can be done by a weighted multi-parameter cost function in the form of \( RO = \sum_i w_{O_i} J_i \), where \( J_i \) are binary variables that indicate whether parameter \( i \) has been violated and \( w_{O_i} \) are non-negative weights which imply the significance of the violation of each parameter \( i \).

If \( RO = 0 \) no violation is assumed, however as \( RO > 0 \) increases the water contamination risk is also increases.
TABLE II
SPECIFICATIONS AND ACCOMPLISHED PERFORMANCE FOR EACH MONITORED PARAMETER

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Measurement principle</th>
<th>Units</th>
<th>Range</th>
<th>Resolution</th>
<th>Accuracy</th>
<th>Quality Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Turbidity</td>
<td>Optical/infrared scattering</td>
<td>NTU</td>
<td>0 – 100</td>
<td>0.1</td>
<td>±0.5</td>
<td>0 – 5</td>
</tr>
<tr>
<td>pH</td>
<td>Galvanic, platinum electrode</td>
<td>mV</td>
<td>-2000 – 2000</td>
<td>2</td>
<td>±10</td>
<td>600 – 800</td>
</tr>
<tr>
<td>Conductivity</td>
<td>Conductive cell</td>
<td>µS/cm</td>
<td>100 – 20000</td>
<td>10</td>
<td>5%</td>
<td>500 – 1000</td>
</tr>
<tr>
<td>Temperature</td>
<td>RTD resistance</td>
<td>°C</td>
<td>-5 – 100</td>
<td>0.1</td>
<td>±0.1</td>
<td></td>
</tr>
<tr>
<td>Flow</td>
<td>Magnetic rotor, hall effect sensor</td>
<td>L/min</td>
<td>1–115</td>
<td>0.0015</td>
<td>15%</td>
<td></td>
</tr>
</tbody>
</table>

As previously indicated, the objective in this paper is to detect anomalies when water quality changes are inside the expected quality ranges by fusing the multi-sensor data. Therefore a risk indicator \( R_I \) function is defined that takes a value \( R_I = 1 \) if a contamination event is detected or \( R_I = 0 \) otherwise.

The first event detection algorithm is denoted as Vector Distance Algorithm (VDA) and the risk indicator \( R_{VDA}^I \) function used in this algorithm is estimated based on the Euclidean distance between the normalized sensor signal vector \( \mathbf{N} \) and the normalized control signal vector \( \mathbf{N}_0 \) of pure (clean) water. Therefore, the risk indicator \( R_{VDA}^I \) is given by

\[
R_{VDA}^I = \begin{cases} 
1 & \text{if } ||\mathbf{N} - \mathbf{N}_0||_2 > d \\
0 & \text{otherwise}
\end{cases}
\]  

(2)

Note that VDA algorithm requires the normalized control signal vector \( \mathbf{N}_0 \) as well as a calibration threshold \( d \) (obtained from a learning phase) to execute.

The second event detection algorithm is denoted as Polygon Area Algorithm (PAA) and the risk indicator \( R_{PAA}^I \) function used in this algorithm is estimated based on the ratio of the polygon area \( A_N \) formed by the \( \mathbf{N} \) vector components (when projected (displayed) on a two-dimensional spider graph with four (TU, ORP, pH, EC) axes starting from the same point) to the polygon area \( A_1 \) formed by the \( \mathbf{1} \) ones vector components (i.e. \( \mathbf{1} = [1111]^T \)). Therefore, the risk indicator \( R_{PAA}^I \) is given by

\[
R_{PAA}^I = \begin{cases} 
1 & \text{if } \frac{A_N}{A_1} > 1 \\
0 & \text{otherwise}
\end{cases}
\]  

(3)

Note that PAA algorithm does not require any further information to execute.

V. EXPERIMENTAL VALIDATION

In this section we present the results of the experimental trials performed to validate the behavior and evaluate the performance of the developed hardware and algorithms on intentional contamination events. The experimental setup consists of the sensor node (central measurement node) that takes samples every 5s from potable water flowing through a flow cell. Intentional contamination of two important contaminants (Escherichia coli bacteria and arsenic) of various concentrations was injected at discrete time intervals and the performance of the event detection algorithms is evaluated on real time. Escherichia coli bacteria and arsenic contamination in drinking water is very severe problem causing serious poisoning to large numbers of people all over the world [18].

![Fig. 7. Experiments with E.coli bacteria contaminated water. (a) Sensors responses to E.coli bacteria. (b) E.Coli bacteria contamination detection.](image)

1) Microbiologically (E.coli) Contaminated Drinking Water: The first experiment considers the case of microbiologically (E.coli) contaminated drinking water. Most E. coli strains are in general harmless to humans, but some types can cause serious food and water poisoning. However, the presence of E.coli is used to indicate that other pathogenic organisms may be present (often of faecal origin). According to WHO guidelines & EU Drinking Water Directive E.coli parametric value is 0 CFU/100mL.

Fig. 7(a) presents the measurements received using the developed sensor node when the following concentrations of E.coli were injected: \( 5 \times 10^{-2}, 5 \times 10^{-1}, 5 \times 10^0, 5 \times 10^1, 5 \times 10^3, 5 \times 10^4, 1 \times 10^7 \) CFU/mL. It is evident that TU and EC sensors responded well when microbiological contaminants injected in chlorinated potable water. ORP sensors has responded with delay and pH sensor has a spiky type of response.
The results of Fig. 7(b) indicate that both algorithms miss the detection of 5 and 10 μg/L because sensors responses were very close to background levels and that the VDA algorithm exhibits two false alarms. Therefore, the performance of PAA algorithm is again better (sharp response, no false alarms) than the VDA algorithm.

Finally, it should be noted that the signatures of normalized sensor outputs can be further processed to minimize false alarms and to identify the type of contaminants, given that a contamination library is available/developed.

VI. Conclusion

In this article, the design and development of a low cost sensor node for real time monitoring of drinking water quality at consumer sites is presented. The proposed sensor node consists of several in-pipe water quality sensors with flat measuring probes. Unlike commercially available analyzers, the developed system is low cost, low power, lightweight and capable to process, log, and remotely present data. Moreover, contamination event detection algorithms have been developed and validated to enable these sensor nodes to make decisions and trigger alarms when anomalies are detected. Such implementation is suitable for large deployments enabling a sensor network approach for providing spatiotemporally rich data to water consumers, water companies and authorities.

In the future, we plan to investigate the performance of the event detection algorithms on other types of contaminants (e.g. nitrates) and install the system in several locations of the water distribution network to characterize system/sensors response and wireless communication performance in real field deployments. Finally, we plan to investigate network-wide fusion/correlation algorithms to assess water quality over the entire water distribution system.

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Fig. 7(b) presents the output signals of the Vector Distance Algorithm (VDA) and Polygon Area Algorithm (PAA). The results of Fig. 7(b) indicate that both algorithms miss the detection of 5 × 10^{-2} CFU/mL because sensors responses were very close to background levels (no anomalies occurred). It should be noted that the performance of PAA algorithm is better and given that it utilizes less information, PAA algorithm is better than the VDA algorithm.

2) Chemically (Arsenic) Contaminated Drinking Water: The second experiment considers the case of chemically (Arsenic) contaminated drinking water. Water contamination by toxic heavy metals and especially arsenic contamination is a common problem encountered in many countries due to undue deposition of mining, agricultural, industrial and urban wastes in water resources. Arsenic is known to affect negatively the mental and central nervous system function, to damage the blood composition, lungs, kidneys, liver, and other vital organs, as well as it contributes to certain neurological degenerative processes and causes skin cancer. According to WHO guidelines & EU Drinking Water Directive Arsenic parametric value is 10 μg/L.

Fig. 8(a) presents the measurements received using the developed sensor node when the following concentrations of Arsenic were injected: 5, 10, 25, 50, 125, 500, 1000 μg/L. Arsenic solutions created from a standard solution of 1000 mg/L As. Unfortunately, almost all sensors did not respond at low arsenic contamination. However, at concentrations above 25 μg/L ORP and pH sensors have responded and at higher concentrations (above 500 μg/L) all sensors responded well. Fig. 8(b) presents the output signals of the Vector Distance Algorithm (VDA) and Polygon Area Algorithm (PAA). The results of Fig. 8(b) indicate that both algorithms miss the detection of 5 and 10 μg/L because sensors responses were very sluggish and close to background levels and that the VDA algorithm exhibits two false alarms. Therefore, the performance of PAA algorithm is again better (sharp response, no false alarms) than the VDA algorithm.

Finally, it should be noted that the signatures of normalized sensor outputs can be further processed to minimize false alarms and to identify the type of contaminants, given that a contamination library is available/developed.

Fig. 8. Experiments with Heavy metals (As) contaminated water. (a) Sensors responses to Heavy metal (As). (b) Heavy metals (As) contamination detection.


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