Distributed Kalman Filter Investigation and Application to Leak Detection in Water Pipeline Monitoring Using Wireless Sensor Networks with Non-intrusive Sensors

Valery Nkemeni, Fabien Mieyeville, Jacques Verdier
University of Lyon, Université Claude Bernard Lyon 1, Ecole Centrale de Lyon, INSA Lyon, CNRS, Ampère, F-69621, Villeurbanne, France
e-mail: valery.nkemeni@etu.univ-lyon1.fr, fabien.mieyeville@univ-lyon1.fr, jacques.verdier@insa-lyon.fr

Pierre Tsafack
University of Buea, Faculty of Engineering and Technology
P.O Box 63, Buea, Cameroon
e-mail: tsafack.pierre@ubuea.cm

***Abstract*— Wireless Sensor Networks (WSN) have found a wide range of applications in monitoring, with most deployments done in a centralized fashion. This results in high energy consumption and latency, as such centralized schemes are characterized by periodic long-distance transmissions. In this work, we demonstrate the benefits of trading off transmission for computation. We propose a solution where local and distributed computing are used to improve the accuracy of anomaly detection in physical systems without the need for long distance transmissions to some central base station. We practically demonstrate this in detecting leaks on a water pipeline testbed, since water losses via leaks is a major problem in most developing countries, including Cameroon. Unlike other works for leak detection in water pipelines available in literature, we build a low-cost sensor node, which is feasible for deployment in developing countries from cheap off-the-shelf commercial elements. The accuracy of the measured vibrations on the surface of pipes is improved using a distributed Kalman filter, where every node independently computes the optimal state estimate used for leak detection by running a local Kalman filter to obtain an accurate local estimate from local measurements and also fusing it with those of its close neighbors. Results show that the distributed Kalman filter improves the reliability of leak detection.**

Keywords- distributed computing; wireless sensor networks; distributed Kalman filter; water pipeline monitoring; non-intrusive sensors.

I. INTRODUCTION

A WSN consists of a number of distributed nodes with sensing, processing and wireless communications capabilities, deployed over an area of interest to monitor physical or environmental conditions. Application areas of WSNs include geographical monitoring, habitat monitoring, transportation, military systems, business processes, microclimate research, medical care and others [1][2]. They are spatially distributed systems that exploit wireless networking as main inter-node interaction channel and are typically constrained in terms of energy, computing power, memory and communication bandwidth.

A. WSN: Shifting towards a distributed approach

Most WSN monitoring applications in literature are centralized [3][4]. This has led to the underutilization of the processing unit and overutilization of the communication unit of sensor nodes since the primarily role of the sensor nodes is to collect and transmit data periodically to an intelligent central base station where all the processing is done in order to detect anomalous behaviors [2][5][6]. In large scale monitoring applications, most of the sensor nodes are geographically far away from the base station and from power supply and are usually battery-driven. The main drawback of such a centralized approach is that of huge energy consumption as periodic transmission of raw data over long distances to the base station leads to fast depletion of sensor node's battery and shortens the lifespan of a WSN [6]-[8]. This is the reason for the numerous research works involved in the development of low energy consumption protocols specifically for WSNs. Other drawbacks include low reliability, longer response time, high bandwidth cost, low level data safety and privacy [6]-[9] [11].

B. The stakes of Water Supply in Developing Countries

Water represents a primary necessity for everyday life and for an effective accomplishment of many industrial processes. In the most remote and isolated regions, as in the most urbanized ones, water provisioning to domestic premises represents a fundamental living necessity. The lack of water may prevent the development of business activities from handicraft manufacturing to goods transformation and energy production [10]. Thus, making accessible potable water is one of the critical essentials to human survival and economic growth of today's society.

In most civilized societies, water transportation via pipelines to clients seems to be the most economical way [12] and consists of water supply systems comprising of two different parts: (1) Transmission mains, which are pipes responsible for transporting water to tanks and (2) Water Distribution Networks (WDN), which pipes and service connections for distributing water to customers. However, these infrastructures are not completely watertight as even in the most recent and well-built WDN, some level of leakage and occasional pipe bursts occur, leading to water

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losses [13]. Water pipeline leakages are one of a few challenges to the water utility companies all over the world. Water loss through leakages is recognized as a costly problem worldwide, due to the waste of precious natural resources, as well as from the economic point of view [14]. A recent report published by the World Bank in 2016 indicated that in developing countries, roughly 45 million cubic meters of water are lost daily with an economic value of over US $3 billion per year. The report also stated that saving half of those losses would provide enough water to serve at least 90 million people [15]. In Cameroon, a developing Sub-Saharan African country, the level of non-revenue water is at 4.67% [16][17]. The reason for this high level of non-revenue water is explained by limited and dilapidated infrastructure that creates physical losses through leaks and/or bursts.

Water demand is increasing continuously and rapidly as a result of the growth of the Earth's population, but water resources are facing a problematical and constant decrease caused by global heating and climate change. Unlike other more peculiar phenomena, water scarcity is common to both developing and developed countries [10]. The scarcity of water thus requires that water losses due to leaks be minimized and if possible, completely eradicated. This has led to enormous research over the years in the field, providing a wide range of methods for detecting and locating leaks in water pipelines.

C. Water Pipeline Monitoring: State of the Art

WSNs for Water Pipeline Monitoring (WPM) consist of a number of sensor nodes with low-cost sensors that periodically collect leak signals from the pipe. The signals are then processed to detect the presence of a leak on the pipeline. The biggest problem with leak detection in WPM using low-cost sensors is that the leak signals may be noisy and may result in false alarms in the leak detection system. Thus, the issue of reliably identifying a leak signal in the midst of errors from a number of sources (commonly called noise) is a fundamental challenge of any leak detection system [18].

A number of centralized schemes for WPM using WSN have been proposed in literature [19]-[22]. The sensor nodes periodically collect leak signals from the pipe where they are installed and transmit to a central base station (where the leak detection algorithm is found) for further processing in order to detect the presence of a leak on the pipeline. Such centralized schemes are characterized by a large number of long-distance transmissions which depletes the sensor node's energy faster.

The purpose of this research is to demonstrate the benefits of trading off communication for computation in WSNs by exploiting the sensor node's processing unit to implement local processing and distributed computing. The role of local processing is to improve the accuracy of measurements made locally whereas distributed computing is there to improve the performance of anomaly detection and to make the WSN to be autonomous without the need for centralized intelligence.

D. Organization of the paper

In this paper, we will present a distributed computing solution for the detection of leaks in water pipelines since water losses due to leaks and/or bursts are a major problem in most developing countries, including Cameroon's WDN. We practically demonstrate our proposed solution on a water pipeline testbed, where we show how distributed computing can be used to minimize the chances of having a false alarm while also maximizing the leak detection sensitivity of the system thereby increasing the performance or reliability of leak detection in WPM. We implement a distributed Kalman filter algorithm [24], on each sensor node as the signal processing approach for filtering the noisy signals collected by the sensors, thus improving the accuracy of leak detection without needing to transmit sensor readings over long distances to a central base station. In our work, distributed computing is implemented using a distributed Kalman filter algorithm and local processing is implemented using a local Kalman filter.

The rest of the paper is organized as follows. Section II reviews some related works in WPM using WSN with non-intrusive sensors. A detailed description of our proposed node architecture and the distributed Kalman filter implemented are presented in Section III. In Section IV, we describe the testbed used to demonstrate our solution, while Section V is involved with the results and discussions and Section VI concludes the paper and highlights the future work.

II. RELATED WORK

In this section, we review some works in literature that are closely related to our study and which made use of WSNs with non-intrusive sensors for leak detection in water pipelines. The survey is based on the node architectures and the leak detection algorithm implemented in each of these studies.

In [19], the authors described PipeNet, a system based on WSNs which aims to detect, localize and quantify bursts and leaks and other anomalies in water transmission pipelines. A laboratory pipe rig was constructed to evaluate and illustrate the detection and localization of leaks using acoustic and vibration data acquired from densely spaced hydrophones and accelerometers installed along the pipeline. The adopted node was based on Intel commercial mote composed of an ARM7 core, a 64KB RAM, a 512 KB Flash, and a Bluetooth radio for communication. Local processing at each node was implemented by using Fast Fourier Transform (FFT) and compression while cross-correlation was implemented at the central server as the leak detection and localization algorithm. Although this work gives a complete solution for WPM, some significant drawbacks could be mentioned. On one hand, the use of Bluetooth radio as the communication technology by this

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work is not an energy-efficient solution. In addition, several high processing algorithms were employed which affect the power consumption of the nodes by accomplishing complex tasks. Besides, despite the fact that data was collected at a very high sampling rate and high frequency, which makes this solution real-time, it leads to an increase in energy consumption of the node. A final drawback is that of adopting a centralized approach.

In [20], the authors reported on the design and development of a multimodal Underground Wireless Sensor Network (UWSN) for pipeline structural health monitoring. The sensor node consisted of a PIC16LF1827 microcontroller, an eRA400TRS 433 MHz transceiver, two temperature sensors and one Force Sensitive Resistor (FSR) pressure sensor. According to the authors, power consumption of the sensor nodes was minimized to 2.2 µW based on one measurement every 6 h in order to prolong the lifetime of the network. Two drawbacks could be highlighted from this work. One is the inability to perform real time monitoring and the other results from adopting a centralized approach for leak detection.

The authors in [21] proposed a solution called EARNPIPE which is comprised of a Leak detection Predictive Kalman Filter (LPKF) and other methods to detect and locate leaks. The data collected from sensors were filtered, analyzed and compressed locally with the same Kalman Filter (KF) based algorithm. A laboratory testbed was constructed using plumbing components and the nodes consisted of an Arduino Due board whose processing unit is based on ARM cortex M3 microcontroller, FSR sensors used for pressure measuring and Bluetooth for communication. The main drawback of this solution is the high-power consumption of the sensor nodes, resulting from the choice of sensor node components such as using power-hungry components like the Arduino Due and Bluetooth as the processing and communication units, respectively. The centralized approach adopted for leak detection and localization is also another drawback as it leads to increase in response time due to latency in delivering processed information and also uneven distribution of energy consumption among nodes in the network [11].

The authors in [22] presented the development of a water pipeline monitoring system using vibration sensors. The experimental setup consisted of a MPU6050 sensor for measurement of vibration occurring along the pipes, an Arduino Uno and Xbee module for wireless transmission to a centralized decision support system. The results of the experiment indicated that, for a pressure of 58.8 kPa, the data recorded by the sensor could distinguish between the presence of a leak and when there is no leak. The drawback of this solution is the high energy consumption at the node level resulting from the choice of power-hungry sensor node components such as the Arduino Uno.

In [23], the authors presented an end-to-end water leak localization system, which exploits edge processing and enables the use of battery-driven sensor nodes. The proposed system combined a lightweight edge anomaly detection algorithm based on Kalman filter and compression rates and a localization algorithm based on graph theory. It was validated by deploying non-intrusive sensors measuring vibrational data on a lab-based water test rig that had controlled leakage and burst scenarios implemented. The sensor nodes were based on Intel Edison development boards and NEC Tokin ultra-high-sensitivity vibration sensors. According to the authors, the edge anomaly detection and localization elements of the systems produce a timely and accurate localization result and reduce the communication by 99% compared to the traditional periodic communication. One main drawback of this work is that the choice commercial element (Intel Edison board) that constitutes the sensor node, is not a cost-effective solution for deployment in developing countries. In addition, the use of Bluetooth as a means of communication by the nodes is not energy efficient.

Given the drawbacks of the solutions proposed in literature, the geographic context of our deployment which is to be done in Cameroon (a third world developing country), and being aware of the fact that the choice of architecture and technology of the sensor node is crucial in determining its performance and power consumption, we seek a solution that is low-cost, feasible and also energy efficient. This will be achieved by first optimizing the computing capacity and power consumption of the sensor nodes by integrating very low consumption processing, sensing and communication units from off-the-shelf commercial components.

III. MATERIALS AND METHODS

Price often has a direct bearing on the quality of a node's sensors and influences the accuracy of the result that can be obtained from a single node [25]. Thus, using low-cost sensors in WPM to detect leak signals is usually characterized by noisy measurements and may result in false alarms in the leak detection system. To minimize the errors in measurement, we chose a one-dimensional Kalman filter to remove the noise and to improve on the accuracy of the measurement made locally at each node. In order to maximize leak detection while minimizing the number of false alarms, a distributed Kaman filter is proposed. In our proposed solution, each sensor node runs a local Kalman filter to obtain an accurate local estimate from the local measurements, then later fuses it with those of its neighbor to achieve a more accurate global estimate used for leak detection. In this way, our proposed solution is autonomous and does not need any central intelligence. To the best of our knowledge, this is the first work that uses WSNs with non-intrusive sensors and a distributed Kalman filter for leak detection in WPM.

In this section, we present a description of the off-the-shelf commercial components that make up the sensor node hardware alongside with the distributed Kalman filter algorithm used to improve on the reliability of leak detection in WPM.

A. Sensor Node Architecture

The architecture and technology of a sensor node is crucial in determining its cost, performance and power consumption. We develop a low-cost and low-power node by integrating cheap and low-power off-the-shelf commercial components. Our proposed node consists of an ESP32 from Espressif Systems as the processing unit, an nRF24L01+ transceiver module from Nordic as the communication unit and an LSM9DS1 Inertia Measurement Unit (IMU) from STMicroelectronics as the sensing unit.

1) ESP32: It is a low-cost, low-power System on a Chip (SoC) series Wi-Fi and dual-mode Bluetooth microcontroller [26]. Engineered for mobile devices, wearable electronics, and Intenet of Things (IoT) applications, ESP32 offers Ultra-Low Power (ULP) consumption through power saving features including fine resolution clock gating, multiple power modes, and power scaling [8]. The ESP32, when active (with the modem being off and CPU being operational), consumes current in the range of 20 mA ~ 68 mA and 10 µA ~ 150 µA in the ULP state (only the RTC memory and RTC peripherals are powered on and the ULP co-processor is functional). The choice of this module is based on our exploration of different sensor node architectures existing in literature [8][27][28]. Some of the features of the ESP32 include: an Xtensa Dual-Core 32-bit LX6 microprocessor operating up to 240 MHz, 520 kB Static Random Access Memory (SRAM), 12-bit Analog-to-Digital Converter (ADC) with up to 18 channels, a built-in Wi-Fi card supporting IEEE 802.11 b/g/n standards, and Bluetooth version 4.2 and Bluetooth Low Energy (BLE). In addition, the ESP32 chip features 40 physical General Purpose Input Output (GPIO) pads, which can be used as general purpose I/O to connect new sensors, or can be connected to an internal peripheral signal [8]. This can permit the coupling of the nRF24L01+ transceiver module to the ESP32, thus making the sensor node to have a complete coverage of the various communication technologies used in IoT. Adafruit ESP32 feather (Huzzah32) is our chosen ESP32 board.

2) nRF24L01+: This transceiver operates in the 2.400 to 2.4835 GHz band and is suitable for wireless applications requiring very low power consumption. It is compliant with the IEEE802.15.4 physical layer protocol, a technical standard which defines the physical layer of low-rate wireless personal area networks. The module connects to a microcontroller to communicate via the SPI interface. With peak RX/TX currents lower than 14 mA, a sub µA power down mode, advanced power management, and a 1.9 to 3.6 V supply range, the nRF24L01+ provides a true ULP solution enabling months to years of battery life from coin cell or AA/AAA batteries. The nRF24L01+ uses Gaussian Frequency Shift Keying (GFSK) modulation [4], with data rates from 250 Kbps to 2 Mbps. The range can be nearly 100m and 500m with and without an external antenna respectively at maximum power [29][30]. It has longer range than Bluetooth, consumes lower power than Wi-Fi and is a cheaper alternative to Zigbee.

3) LSM9DS1: It is a 9 Degree of Freedom (DOF) IMU which features a 3D digital linear acceleration sensor, a 3D digital angular rate sensor, and a 3D digital magnetic sensor. The LSM9DS1 has a linear acceleration full scale of ±2g/±4g/±8g/±16g, a magnetic field full scale of ±4/±8/±12/±16 gauss and an angular rate of ±245/±500/±2000 dps. It includes an I^2C serial bus and an SPI serial standard interface for interfacing with the microcontroller. It has analog supply voltage ranging from 1.9 V to 3.6 V and the current consumption of the accelerometer in normal mode is 600 uA [31].

B. Configuration of the Node

The nRF24L01+ transceiver module and LSM9DS1 IMU sensor are interfaced with the ESP32 via the SPI and I^2C interfaces, respectively. The sensitivity of the accelerometer in the LSM9DS1 sensor is configured to ±2g since this has the highest sensitivity, which makes it most appropriate for detecting vibrations of smaller magnitude such as those on the surface of water pipe. The accelerometer collects the vibration in 3D, that is in the X, Y and Z direction given by A_x, A_y and A_z, respectively. The magnitude of the vibration on the surface of the pipe was computed by taking the resultant of the acceleration in all three directions.

C. Distributed Kalman Filter Algorithm

Kalman filtering is a technique of filtering information which is known to have some error, uncertainty, or noise. The goal of the filter is to take in this imperfect information, sort out the useful parts of interest, and reduce the uncertainty or noise [32]. There are two types of noise associated with stochastic estimation, process noise and measurement noise. Process noise can be explained as the difference between the real system and the model, while the measurement noise is the noise associated with the sensors and instrumentation. The Kalman filter minimizes the estimated error covariance in a linear stochastic system, has low memory requirements and low complexity [33], and it is capable of handling situations with a lot of noise or high uncertainty in the data. This thus makes it a perfect candidate for improving the accuracy of noisy measured leak signal and detecting leaks in WPM using WSNs, as nodes are constrained in memory, processing power and energy [23][33][34]. Thus, to remove noise from the readings obtained by the IMU sensors and improve on the accuracy of measurement, we propose the use of a one-dimensional Kalman filter.

The Kalman filter is based on two steps, comprising of a prediction followed by a correction in order to determine the states of the filter. This is sometimes called predictor-corrector, or prediction-update [32].

In the first step, the estimated state x, at time k is predicted from the updated state at time k-1. The prediction of the current state and the covariance matrix is given by [32] [33]:

$$\hat{x}_k^- = A\hat{x}_{k-1} + Bu_k \tag{1}$$

$$P_k^- = A.P_{k-1}.A^T + Q_k \tag{2}$$

where $\hat{x}_k^-$ is the predicted state vector at time k, $\hat{x}_{k-1}$ is the previous estimated state vector, P_k^- represents the predicted state error covariance matrix, A and B are matrices defining the system dynamics, u_k is the input vector, P_{k-1} is the previous estimated state error covariance matrix, and Q is the process noise covariance matrix.

The second step is the correction or update step. This step aims to get an improved estimate by incorporating new measurements into the predicted estimate using the Kalman gain (K_k).

$$K_k = \frac{P_k^- H^T}{(HP_k^- H^T + R_k)^{-1}} \tag{3}$$

$$\hat{x}_k = \hat{x}_k^- + K_k(z_k - H\hat{x}_k^-) \tag{4}$$

$$P_k = (I - K_k H)P_k^- \tag{5}$$

where H is a matrix necessary to define the output equation, R is the measurement noise covariance, I is an identity matrix, $\hat{x}_k$ is the estimated or updated state vector, z_k is the measurement at time k and P_k is the updated state error covariance.

In the model equation, A and B are constants since we are dealing with a one-dimensional Kalman filter. H is 1 because it is known that the measurement is composed of the state value and some noise, while A is 1 because it is assumed that the next value will be the same as the previous one. We derived R from the LSM9DS1 datasheet. The linear acceleration typical zero-g level offset accuracy given in the datasheet is ± 90 mg, thus R is 0.09. Q is obtained after some experimentation. From the datasheet, the sensor in a steady state on a horizontal surface will measure 0 g on both the X-axis and Y-axis, whereas the Z-axis will measure 1 g. We did some experiments with different Q values and selected the one that best approximated the acceleration values at zero-g. Q equal to 0.001 best approximated the zero-g acceleration values.

After noise removal, leaks can be detected accurately. To maximize leak detection and minimize the number of false alarms without using any form of centralized scheme, we proposed the use of a distributed Kalman filter.

A number of distributed Kalman filter algorithms have been presented in literature [24][34]-[36]. In our solution, we implemented the distributed Kalman filter algorithm proposed in [24]. The authors in [24] presented a novel event-triggered distributed state estimator based on a consensus Kalman filtering approach, as well as a transmission triggering condition which essentially requires that the local estimate and/or covariance of a given node be sufficiently far away from the ones computed by neighbors before there can be exchange of data between a node and its neighbors. The paper addresses Distributed State Estimation (DSE) over a network in which each node can process local data as well as exchange data with neighbors. In their proposed DSE algorithm, each node runs a local Kalman filter and then, in order to improve its local estimate, fuses the local information with the one received from its in-neighbors [24].

The implemented distributed Kalman algorithm starts by updating a local information pair (local estimate and state error covariance matrix) in the correction step. In the information exchange step, each sensor node determines whether to transmit its information pair to its out-neighbors or not based on the value of its transmission flag. The transmission flag is set when the discrepancy between the current updated local estimate and the last transmitted local estimate is larger than some threshold, which can be varied to achieve a desired behavior in terms of transmission rate and performance. This means that the data currently computed by a node's out-neighbors are no longer consistent with the data locally available at the node. The transmission test is designed so as to ensure that, in the case of no transmission, the data currently computed by the out-neighbors of a node are close to the data locally available at the node, both in terms of mean and covariance. Thus, the idea is to selectively transmit only when the discrepancy is large. In the information fusion step, a node computes a fused information pair from its local information pair and those received from in-neighbors at time step k. For in-neighbors that did not transmit based on their transmission flag not being set, the node computes an approximate local pair for such nodes from the latest local information pair received from them. Finally, in the prediction step, the fused information pair is propagated in time by applying the Kalman filter prediction step to compute the local predicted information pair at time k+1.

The distributed Kalman filter algorithm is implemented on a network of two nodes with addresses given by 00 and 01 (octal representation) with the node 00 being the base node or Personal Area Network (PAN) coordinator. The nodes, having the Adafruit feather ESP32 (Huzzah32) microcontroller as the processing unit, are programmed with the Arduino C programming language using the Arduino 1.8.9 Integrated Development Environment (IDE). It should be noted that Adafruit recommends the programming of the Huzzah32 board using the Arduino IDE. The RF24Network and RF24 libraries by TMRh20 are used to control the nRF24L01+ transceiver interfaced to the Huzzah32 via SPI. The firmware uploaded to the nodes after compiling the distributed Kalman filter algorithm using the Arduino IDE occupied a storage space of 225 KB. Global variables use 15 KB of dynamic memory, leaving 312 KB for local variables. The implementation did not make use of any operating system, but that will be done in future work.

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IV. EXPERIMENTAL SETUP

To practically demonstrate our proposed solution, a laboratory testbed, whose configuration is similar to that of a WDN in Cameroon, was built at the Electrical and Electronic Laboratory of the University of Buea, Cameroon. It consists of two plastic water storage tanks of capacity 1000 L (one being a storage tank placed on a tower of height 9 m and the other being a supply tank placed beneath the tower), a U shaped 13m long PVC pipe having an external diameter of 32 mm and an internal diameter of 30 mm, and an electrical pump with 0.7 Hp motor providing a maximum pump capacity of 40 L/min for filling the upper storage tank. Leakage in the pipeline was induced by opening a valve placed some 4 m away from the inlet of water into the system. Figure 1 displays the testbed setup.

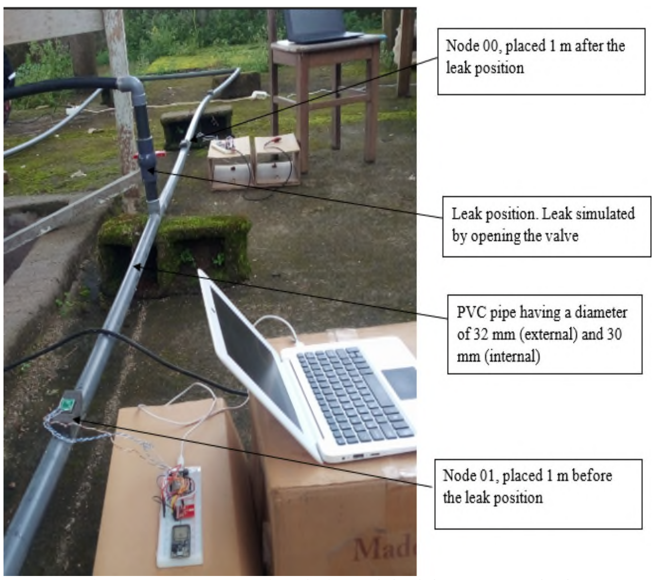
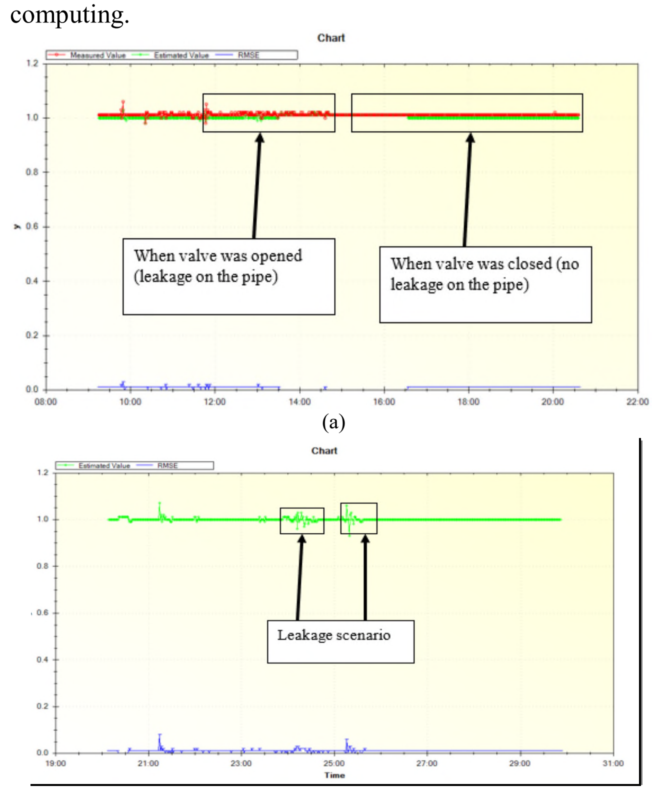


Figure 1. A cross-sectional view of the laboratory testbed.

Our setup consists of two sensor nodes namely Node 00 placed 1 m after the leak position and Node 01 placed 1 m before the leak position, as shown in Figure 1. The mechanical coupling between the pipe and IMU was done by first attaching the IMU firmly to a polyurethane foam to form a single entity. The entity was then glued to the pipe. The role of the IMU sensors is to measure vibrations on the surface of the pipe in the form of acceleration.

V. RESULTS AND DISCUSSION

In this section, we discuss the laboratory deployment results. To measure the performance of our leak detection solution using distributed Kalman filter algorithm, we simulated a leak at a single location along the pipeline, as shown in Figure 1. We used two sensor nodes, one placed 1 m before and the other placed 1 m after the leak position. In this deployment, the leak location is fixed, but we could vary the locations of the sensors to measure the effectiveness of our solution with different sensor positions. We carried out measurements for three scenarios: no Kalman filter implementation, local Kalman filter implementation and distributed Kalman filter implementation. For these experiments, we took traces of data collected from the two sensors, and compared the effectiveness of the approach, that is the effect on leak detection when the sensor nodes implemented distributed computing and the case where they implemented only local computing. In the case of local computing, the nodes run only a local Kalman filter for improving the accuracy of local measurements. In this scenario, each of the sensor node predicts the next state from the previous state and then collects local measurement which is then used to update the predicted state to obtain a more accurate local estimate. There is no exchange of local estimates between nodes in the case of local computing. However, with distributed computing, each of the sensor nodes first obtains its local estimate by performing local computing. In order to achieve a more accurate estimate, the node then shares its local estimate with its neighbor and also fuses its local estimate with the local estimate received from its neighbor. Figure 2 represents the data obtained from Node 00 (sensor after leak position) when the distributed Kalman filter algorithm was implemented on both sensor nodes while Figure 3 represents the results obtained when only a local Kalman filter was implemented on both sensor nodes without distributed computing.



(a)

(b)

Figure 2. Estimated acceleration from Node 00 with measured acceleration (a) and without measured acceleration (b) when distributed Kalman filter was implemented

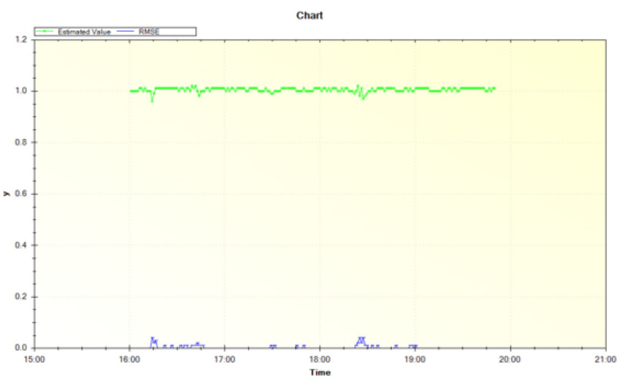


Figure 3. Estimated acceleration from Node 00 when distributed Kalman filter was not implemented

From preliminary results obtained in the field, the estimated acceleration of the pipe when there is no leakage is below 1.01 g while an estimated acceleration greater than 1.01 g corresponds to a leakage on the pipe. This is because when there is a leak, the flow turbulence increases and this is significantly responsible for the vibrations of the pipe walls, since the source of vibration is dissipated energy caused by turbulence.

Comparing the results in Figure 2 (where distributed Kalman filter is used) with those of Figure 3 (where only local Kalman filter is used), reveals that a leakage scenario can be isolated from a non-leakage scenario in the case where distributed Kalman filter is used. This increases the performance or reliability of detecting leaks and minimizes the rate of false alarms. However, it is difficult to distinguish a leakage scenario from a non-leakage scenario when only a local Kalman filter is used. The data displayed in Figure 3 has higher likelihood of producing false alarms since the estimated acceleration computed by the local Kalman filter is still having a lot of uncertainties. As shown in Figure 3, the estimated acceleration is fluctuating rapidly over short time periods. Applying the fixed threshold acceleration of 1.01 g will result in a higher rate of false alarms. This leads to multiple alarms and associated alarm clears as an alarm is declared each time the estimated acceleration fluctuates above the threshold value of 1.01 g and as it fluctuates back below the threshold, the alarm clears.

In our implementation, the Kalman filter performs 10 iterations to compute an optimal local estimate. When there is no leakage, the measured acceleration on the pipe surface is 1.00 g while the estimated acceleration on pipe surface after performing Kalman filtering is 0.99 g.

VI. CONCLUSION AND FUTURE WORK

This paper demonstrates the benefits of trading off long-distance transmission for computation. We propose a solution where local and distributed computing are used to improve the accuracy of anomaly detection without the need for long distance transmission to some central base station. We practically demonstrated this in detecting leaks on a water pipeline testbed.

In terms of sensor node architecture, unlike other works for WPM using WSNs available in literature, we developed a low-cost sensor node, which is feasible for deployment in developing countries, from cheap off-the-shelf commercial elements. The sensor node is composed of an ESP32 microcontroller as the processing unit, an nRF24L01+ transceiver module as the communication unit, and an LSM9DS1 IMU as the sensing unit.

In terms of leak detection algorithm, we use a distributed Kalman filter. Each node independently computes the optimal state estimate used for leak detection by running a local Kalman filter to obtain an accurate local estimate from local measurements and also fusing it with those of its close neighbors. As indicated in the results obtained, this improved on the accuracy of the vibrations measured on the surface of the pipes using the IMU and increased the reliability or performance of leak detection in WPM using WSNs without needing to transmit data over long distances to some central base station.

As future work, we intend to measure and establish an energy profile of the sensor node, where the energy consumption of each of the components that make up the sensor node is taken into consideration. This will enable us to estimate the energy consumption of the sensor node when it is in the idle mode, when it is in computing mode, and when it is transmitting. The end product will be a benchmark that can be used to evaluate the performance and energy consumption of different distributed algorithms. This will provide insights on how different distributed algorithms affect the performance and lifetime of a WSN. In addition, we are currently working on implementing the distributed Kalman filter algorithm as a multithreaded application on the ESP32 using the real-time operating system FreeRTOS [37]. We will investigate the effect of using FreeRTOS on the performance and energy consumption of the sensor node and also analyze the scenarios associated with consumption measures, in order to establish the energy performance of the proposed solution.

REFERENCES

[1] S. R. Jino Ramson and D. J. Moni, "Applications of Wireless Sensor Networks – A Survey" International Conference on Innovations in Electrical, Electronics, Instrumentation and Media Technology (ICEEIMT), Nov. 2017, pp 325-329.

[2] T. Devanaboyina, B. Pillalamarri, and R. M. Garimella, "Distributed Computation in Wireless Sensor Networks: Efficient Network Architectures and Applications in WSNs," International Journal of Wireless Networks and Broadband Technologies, vol. 4, no. 3, pp. 14-19, Jul. 2015.

[3] H. Huang, "Distributed Computing in Wireless Sensor Networks," in Encyclopedia of Mobile Computing and Commerce, pp. 202-206, 2007.

[4] P. Costa, L. Mottola, A. L. Murphy, and G. P. Picco, "TeenyLIME: transiently shared tuple space middleware for wireless sensor networks," In: Proceedings of the international workshop on middleware for sensor networks, ACM, pp. 43-48, 2006.

[5] F. Mieyeville, D. Navarro, and O. Bareille, "Autonomous Wireless Sensor Network for distributed active control," IEEE Vehicle Power and Propulsion Conference (VPPC), pp. 1-6, Dec. 2017.

[6] W. Zhang, B. Chen, H. Song, and L. Yu, “Distributed Fusion Estimation for Sensor Networks with Communication Constraints,” 2016, doi: 10.1007/978-981-10-0795-8_1.

[7] D. Datla, X. Chen, T. Tsou, and S. Raghunandan, "Wireless Distributed Computing: A Survey of Research Challenges," Communications Magazine, IEEE, vol. 50, no. 1, pp. 144-152, 2012.

[8] M. A. Quintana-Suárez , D. Sánchez-Rodríguez, I. Alonso-González, and J. B. Alonso-Hernández, "A Low Cost Wireless Acoustic Sensor for Ambient Assisted Living Systems," Applied Sciences, vol. 7, no. 877, pp. 1-15, 2017.

[9] A.C. Sankaranarayanan, R. Chellappa, and R. G. Baraniu, "Distributed Sensing and Processing for Multi-Camera Networks," in Distributed Video Sensor Networks, London, Springer, 2011.

[10] A. R. Iyeswariya, R. M. Shamila, M. JayaLakshmi, K. Maharajan, and V. Sivakumar, "A study on Water Leakage Detection in buried plastic pipes using Wireless Sensor Networks," International Journal of Scientific & Engineering Research, vol. 3, no. 10, Oct. 2012.

[11] E. D. Pascale, I. Macaluso, A. Nag, M. Kelly, and L. Doyle, "The Network as a Computer: a Framework for Distributed Computing over IoT Mesh Networks," IEEE Internet of Things Journal, vol. 5, no. 3, pp. 2107-2119, 2018.

[12] M. Z. Abbas, K. A. Baker, M. Ayaz, and H. Mohamed, "Key Factors Involved in Pipeline Monitoring Techniques Using Robots and WSNs: Comprehensive Survey," Journal of Pipeline Systems Engineering and Practice·, 2018.

[13] L. Ribeiro, J. Sousa, A. S. Marques, and N. E. Simões, "Locating Leaks with TrustRank Algorithm Support," Water, vol. 7, pp. 1378-1401, 2015.

[14] K. B. Adedeji , Y. Hamam, B. T. Abe, A. and M. Abu-Mahfouz, "Towards Achieving a Reliable Leakage Detection and Localization Algorithm for Application in Water Piping Networks: An Overview," IEEE Access, pp. 20272 – 20285, 2017.

[15] C. Bell, "The World Bank and the International Water Association to Establish a Partnership to Reduce Water," World Bank, 2016. [Online]. Available: http://www.worldbank.org/en/news/press-release/2016/09/01/the-world-bank-and-the-international-water-association-to-establish-a-partnership-to-reduce-water-losses. [Accessed 03 September 2019].

[16] African Development Bank Group, "Africa Infrastructure Knowledge Program," 01 January 2016. [Online]. Available: http://www.afdb.org/en/. [Accessed 03 September 2019].

[17] Y. H. Blaise, “Suffering for water, suffering from water: access to drinking-water and associated health risks in Cameroon,” J. Health Popul Nutr. Vol. 28, No. 5, pp. 424–435, 2010.

[18] M. Henrie, P. Carpenter, and R. E. Nicholas, Pipeline Leak Detection Handbook, Elsevier, Cambridge, MA 02139, United States, 2016.

[19] I. Stoianov, L. Nachman, S. Madden, T. Tokmouline, and M. Csai, “PIPENET: A Wireless Sensor Network for Pipeline Monitoring,” 6th International Symposium on Information Processing in Sensor Networks, Apr. 2007.

[20] A. M. Sadeghioon, N. Metje, D. Chapman, and C. Anthony, “SmartPipes: Smart Wireless Sensor Networks for Leak Detection in Water Pipelines,” J. Sens. Actuator Netw. Vol. 3, pp. 64-78, 2014.

[21] F. Karray, A. Garcia-Ortiz, M. W. Jmal, A. M. Obeid, and M. Abid. “EARNPIPE: A Testbed for Smart Water Pipeline Monitoring using Wireless Sensor Network,” Computer Science, vol. 96, pp. 285 – 294, 2016.

[22] M. Ismail, R. A. Dziyauddin, and N.A. Ahmad. “Water pipeline monitoring system using vibration sensor”, IEEE Conference on Wireless Sensors (ICWiSE), pp. 26-28, Oct. 2014.

[23] S. Kartakis, W. Yu, R. Akhavan, and J. A. McCann, “Adaptive Edge Analytics for Distributed Networked Control of Water Systems,” First International Conference on Internet-of-Things Design and Implementation (IoTDI), Apr. 2016.

[24] G. Battistelli, L. Chisci, and D. Selvi, "A distributed Kalman filter with event-triggered communication and guaranteed stability," Automatica, vol. 93, pp. 75–82, 2018.

[25] H. Karl, and A. Willig, Protocols and Architectures Wireless Sensor Networks, John Wiley & Sons, 2005.

[26] Expressif Systems, "ESP32 SoC," [Online]. Available: https://www.espressif.com/en/products/hardware/esp32/overview. [Accessed 03 September 2019].

[27] F. Karray, M. W. Jmal, A. Garcia-Ortiz, M. Abid, and A. M. Obeid "A comprehensive survey on wireless sensor node hardware platforms," Computer Networks, vol. 144, p. 89–110, Oct. 2018.

[28] A. Maier, A. Sharp, and Y. Vagapov. “Comparative Analysis and Practical Implementation of the ESP32 Microcontroller Module for the Internet of Things,” Internet Technologies and Applications, pp. 143-148, 2017.

[29] Nordic Semiconductor, ―nRF24L01+ Single Chip 2.4GHz Transceiver Product Specification v1.0, September 2008, available at https://www.sparkfun.com/datasheets/Wireless/Nordic/nRF24L01P_Product_Specification_1.0, [Accessed 03 September 2019].

[30] H. Saha, S. Mandal, S. Mitra, S. Banerjee, and U. Saha, “Comparative Performance Analysis between nRF24L01+ and XBEE ZB Module Based Wireless Ad-hoc Networks”, I. J. Computer Network and Information Security, vol. 7, pp. 36-44, 2017.

[31] STMicroelectronics, --- LSM9DS1 Datasheet, DocID025715 Rev 2, November 2014, available at https://www.st.com/resource/en/datasheet/DM00103319, [Accessed 03 September 2019].

[32] M. B. Rhudy , R. A. Salguero and K. Holappa, "International Journal of Computer Science & Engineering Survey (IJCSES) , vol. 8, no. 1, 2017.

[33] F. Karray, M. W. Jmal, and M. Abid, “High-performance Wireless Sensor Node Design for Water Pipeline Monitoring,” in The Eleventh International Conference on Mobile Ubiquitous Computing, Systems, Services and Technologies, 2017.

[34] Y. He, S. Li, and Y. Zheng, "Distributed State Estimation for Leak Detection in Water Supply Networks”," IEEE/CAA Journal of Automatica Sinica, 2017.

[35] D. Marelli, M. Zamani, M. Fu, and B. Ninness, "Distributed Kalman filter in a network of linear systems," Systems & Control Letters, vol. 116, pp. 71–77, 2018.

[36] Z. Wu, M. Fu, Y. Xu, and R. Lu, “A distributed Kalman filtering algorithm with fast finite-time convergence for sensor networks” Automatica, vol. 95, pp. 63–72, 2018.

[37] O. Hahm, E. Baccelli, H. Petersen, and N. Tsiftes, “Operating Systems for Low-End Devices in the Internet of Things: A Survey,” IEEE Internet of Things Journal, vol. 3, no. 1, pp. 720 - 734, 2016.