Event Detection and localization in Urban Water Distribution Network

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***Abstract*—Urban water supply and distribution system infrastructure is aging rapidly and the frequency of pipe burst increases. These events can be very expensive due to water supply disruptions, and damage to surrounding properties and infrastructures. Therefore, methods of detecting and localizing underground burst events in real time can be very helpful in mitigating these impacts. In this research, a cost-effective wireless sensor network was developed for real time monitoring, analyzing and modeling of urban water distribution systems. This paper presents an application of a proposed Joint Time Frequency Analysis for detecting events in water distribution pipelines. The idea behind this method is based on the detection of pressure fluctuations induced by the burst. This proposed approach for event detection employs a spectrogram, one of the Joint Time Frequency Analysis approaches. The feasibility of the proposed method is tested through emulated leak-off experiments and is validated with monitoring data in an operational system. The results demonstrate that the proposed method has the potential to assist in the management water infrastructure by monitoring existing conditions and providing real-time feedback in case of the failure.**

***Index Terms*—Event Detection, Joint Time Frequency Domain Analysis, Spectrogram, Gabor Transform.**

I. Introduction

RAPID growth of urban population, water scarcity, combined with aging infrastructures increases the necessities for the smart water infrastructures for the authorities. In 2008, more than half of the human population is living in cities. Urban population growth is at an unprecedented rate in the developing countries. Urban infrastructures such as transportation network, drinking water distribution system, sewer system are critical to sustain the quality of urban life. For long-term sustainability of the environment, cities need to manage complex, aging infrastructures efficiently. According to United Nation Human Development Report 2006, more than 1.2 billion people lack access to clean drinking water. Therefore, the effective management of water infrastructure is one of the main challenges for water authorities. Recently, in many U.S. cities, water main burst is a critical issue with failing infrastructure. In September 2009, Maryland experienced a huge (72-in) water main burst under a road, sending muddy water over neighborhood streets and down highway ramps. Nearly 1,000 customers were without power. In December 2013, a series of water main bursts occurred in the downtown area of Jersey City. The time and location of the burst was not immediately able to be determined. Dozens of families were without water. The lack of real-time monitoring, detection and localization system caused the repaired crews to dig underground to find the broken pipe.

Based on these examples, it is necessary to have real-time event detection and localization system to assess the condition of water distribution system infrastructure.

1) To effectively detect the leak so as to minimize the water loss and conserve energy
2) To accurately locate the leak so as to initiate the subsequence progress of isolating the affected area and repair the corresponding pipes.
3) To notify the utility operator to effectively react so as to prevent further damage and isolate the affected area.

The primary sources of water losses within distribution systems are associated with leaks and bursts in the underground pipe network and arise from a range of mechanisms including material corrosion, fatigue associated with water pressure fluctuations, structural failures caused by ground movements or erosion of soil support, or excessive surface loading from traffic etc. Apart from water shortages, leakage in water transmission pipes imposes many associated dilemmas, such as financial loss, water quality issues and ensuing damage and harm to public safety. Among these problems, economic losses include direct costs from water loss, costs of producing unpaid water, repair costs, costs associated with service disruption and intangible costs such as customer dissatisfaction, water quality impairment and public safety. Therefore, leak detection and localization have become imperative activities for water authorities. A total of 27% of real loss has been due to unaccounted for water [1]. To mitigate water losses during transmission, a better approach to leakage management is necessary. Extensive research has been carried out on this topic for more than two decades. Several numerical studies [2] [3] and computer simulation methods [4] [5], as well as numerous laboratory and field experiments [6] [7] [8], have been carried out. Leak detection methods can be categorized into active techniques which address unreported losses of water, and passive methods to address reported ones.

Active leak detection systems comprise the analysis of the hydraulic characteristics of a pipeline system (acoustic signals, vibration, flow and pressure measurements), whereas passive leak detection methods are carried out by visual inspections of sites. The visual inspection approach is inefficient because it takes a certain amount of time for water from a leak to be visible on the ground. Apparently, a smaller leak takes longer to become visible. In certain cases, the appearance of water from a small leak may take up to two years. Moreover, this approach is not applicable during normal operation, is time-consuming and costly, and is unable to be deployed on a continuous basis.

Among active leak detection methods, the acoustic leak detection method [9] [10] is commercially adopted to verify a suspected leak and to pinpoint the location of the leak by listening to sounds on the pavement or soil above the water pipes. Although it can accurately pinpoint the location of a leak, its performance is affected by the type of pipe material and interference from road traffic and other sources. Moreover, this method requires a dense sensor network, and acoustic signals have excessive signal attenuation, which makes this method infeasible for continuous monitoring. Therefore, analyzing the transient behavior of a system to detect leaks has been identified as a popular research area because this technique possesses the immense benefit of being able to monitor continuously which has been proven by PIPENET [11] and the Water-WiSe@SG [12] project. Different researchers have analyzed different characteristics of hydraulic pipeline systems (acoustic, pressure and flow measurements). All of these methods apply fundamental signal processing functions, such as cross-correlation [13] , wavelet transforms [14] [15] (Continuous, Discrete), Fast Fourier Transform (FFT) [16] [17] [18] [19] and Cepstrum Analysis [20], in conjunction with other sophisticated mechanisms (Artificial Neural Network (ANN), Support Vector Machine (SVM) and Genetic Algorithm (GA)) to achieve an individual goal.

In 1992, Pudar and Liggett [21] introduced the inverse steady state analysis method. Inverse Transient Analysis (ITA) is one of the first leak detection methods to use the inverse method for pressure measurements. ITA identifies the presence of the leak and its location by analyzing the transient pressure wave of the pipeline. The drawback of this ITA method is that performance is highly reliant on the hydraulic model employed. Covas extended this method to estimate the leak flux associated with sudden burst events by using flow and pressure measurements and an optimization algorithm amalgamated with closed loop network topology (referred to as a District Metered Area [DMA]) and a Supervisory Control And Data acquisition (SCADA) system. The prerequisite for this method is that it must be used in conjunction with DMA and the network with a well-calibrated model. In 2000, Vitkovsky [22] proposed the implementation of Genetic Algorithm (GA) for ITA to improve the efficiency of the optimization algorithm. Their experiments on a test program showed that this scheme is effective under a controlled environment and detects leaks at nodal locations.

Misiunas [23] [24] suggested an alternate version of a transient-based leak detection methodology in which the pipeline system is monitored periodically to discern anomalies (leaks, bursts, blockages, etc.). The method was validated on a water transmission pipeline with a single dead-end pipe. However, the applicability of the method in a real water distribution network needs to be investigated, and the timing window for the initial transient reference model needs to be calibrated in order to achieve good results.

Mpesha [17] [18] initiated a method to analyse the signal in the frequency domain, Frequency Response Analysis (FRA). In the FRA approach, a transient signal is first created and then transformed to the frequency domain using FFT. Next, the Frequency Response Diagram (FRD) of the system is built to detect the presence of a leak. The primary pressure amplitude peak in the FRD indicates the system resonance peak, whereas the secondary peak indicates the leak resonance peak. Lee [2] [25] validated the relevance of his previous research on leak detection using a FRD with numerical studies for different sorts of systems. Similarly, Ferrante and Brunone [26] established wavelet analysis of experimental data to expose the singularity, which is the indication of the occurrence of a burst. Beck et al. [13] recommended the application of a cross-correlation method to the analysis of a reflected pressure wave to identify the features (junction, branch, node, etc.) of pipelines and leaks. Ferrante et al. [27] continued their research on the effectiveness of different wavelet techniques for pipeline diagnosis with both numerical studies and experiments.

Alternatively, Xin-Lei et al. [28] developed an enhanced version of wavelet analysis (threshold self-learning wavelet method) for pipeline leak detection by means of de-noising the signal. Tang [29] also applied a wavelet analysis to de-noise the signals acquired from vibration sensors, which are assumed to be linked to the onset of a leak using a cross-correlation method. Srirangarajan et al. [30] proved the applicability of wavelet transform for leak detection and approximation of the leak location on an operating water distribution system. All of these burst detection methods work well under certain controlled conditions. In addition, the fidelity of each method is largely limited by underlying constraints. In essence, all leak detection and localization methods have the same drawback associated with their reliance on the system characteristics apart from internal and external background noises. In time domain, the signal is represented as a function of time. The analysis of signals in the time domain is rather subjective and largely reliant on prior experiences. In frequency domain, the signal is represented as a function of frequency by performing Fourier transformation, which shows how quickly the signal magnitude changed. The pressure transient signals comprise non-periodic signal which changes its frequency contents over time. Therefore, it is far more useful to characterize the signal in time and frequency domains simultaneously. Therefore, we employ joint time-frequency analysis (JTFA) [31] to identify the presence of leaks.

One of the most popular application of JTFA is speech signal processing. The other applications includes study of detection of radio frequency (RF) non-linear chirp-type signal, radar image processing, biomedical signal processing, economy and ecology data analysis.

This paper presents a novel approach for detecting leaks and bursts within an urban water distribution system. The proposed approach is based on a spectrogram approach together with the Gabor transform [32] to filter the noise from the results and hence, enhance the capability of the proposed JTFA algorithm to detect leaks. The proposed approach is simple and easy to implement. It does not require a sophisticated model of the system. Moreover, this approach has been developed and tested

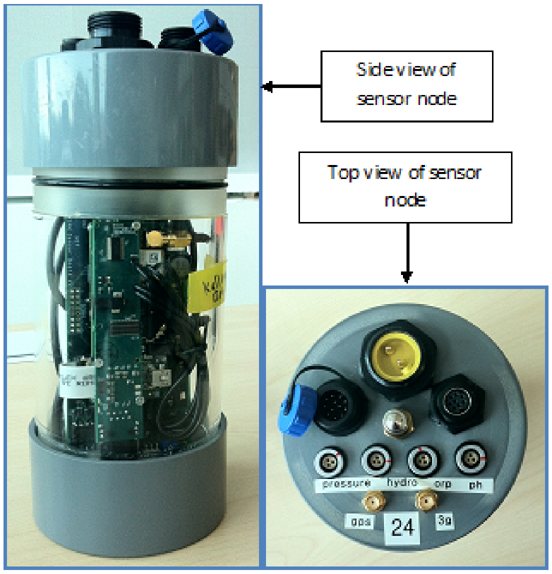

Fig. 1. WaterWiSe@SG sensor node collecting pressure, hydrophone, pH and ORP data.

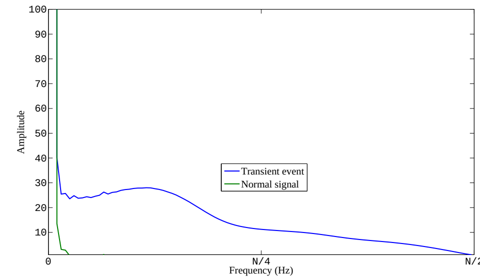

Fig. 2. Fourier Transform of normal pressure signal and transient signal. N is the number of FFT point

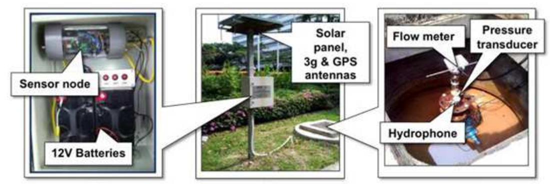

Fig. 3. WaterWiSe@SG sensor node deployment: (from left to right) the sensor node and batteries, the enclosure and solar panel mounting and the tapping point attaching the sensors to the pipe

on a real Water Distribution System (WDS) in Singapore.

II. System Design and Implementation

The Wireless Water Sentinel project in Singapore (WaterWiSe@SG) [36] is a large scale wireless sensor network for urban water distribution system designed to serve as a decision support system, a hydraulic test-bed and a real time monitoring system. The current test-bed comprises more than 35 sensor nodes covering 60 km^2 in the FPCH water distribution zones of Singapore. The WaterWiSe@SG project aims to develop a generic wireless sensor network to monitor the water distribution network in a continuous manner with the following goals:

1) Deployment of a cost-effective wireless sensor network for high data acquisition rate, on-line monitoring of hydraulic and water quality parameters within a large urban water distribution network;
2) Remote detection of leaks and pipe burst events with sophisticated data mining algorithms; and
3) Real-time pressure and flow measurements from the sensor network to improve state estimation of the network using a hydraulic model.

WaterWiSe@SG test-bed was designed to continuously monitor the water distribution system in real time. Therefore, sensor nodes comprising hydraulic (flow and pressure) and water quality (pH and oxidation reduction potential (ORP)) sensors were deployed in a section of downtown Singapore. These sensor nodes are attached to the water distribution pipes to measure, collect the data. The data is divided into 30 seconds files and compressed before transmitting to the back-end data server for archival and processing. All the sensor nodes (Figure. 1) are time-synchronized using Global Positioning System (GPS). The WaterWise@SG test-bed enables online hydraulic modeling, leak-off experimentation and operational event analysis. Several leak-off experiments have been performed using the WaterWiSe@SG test-bed to verify the applicability of the leak detection and localization algorithm.

III. Joint Time Frequency Analysis for Event Detection

This method employs the JTFA of the pressure transient signals. Fourier transform provides an efficient tool for observing a signal in the frequency domain. According to the compression/expansion relationship between time and frequency, an event that occurs faster in time is composed of a higher frequency [33]. Because the transient signal occurs within a short period of time, it contains more high-frequency components than does the normal signal (Figure.2).

However, Fourier transform is only an average of the frequency content over time. To display the frequency content as a function of time, a spectrogram (one of the JTFA methods) is used. JTFA is a set of transforms that map a one-dimensional time domain signal into a two-dimensional representation of energy versus time and frequency.

Therefore, we propose a JTFA method to identify leaks in water distribution networks. The method uses a Joint Time Frequency Analysis (JTFA) to detect the pressure transient signals induced by leaks. Because these transient signals are less prone to noise, the detectable range is much wider than that of acoustic signals. These signals are obtained from WaterWiSe@SG [34] wireless sensor network currently installed in the Fort Canning and Pearl's Hill distribution zones in Singapore.

First, the raw transient signals are acquired by the pressure sensors 3 attached to the water distribution pipelines. According to the initial calculation, we sampled and collected the data at 2kHz. However, after through investigation of its effects on event detection and localization, a lower sampling

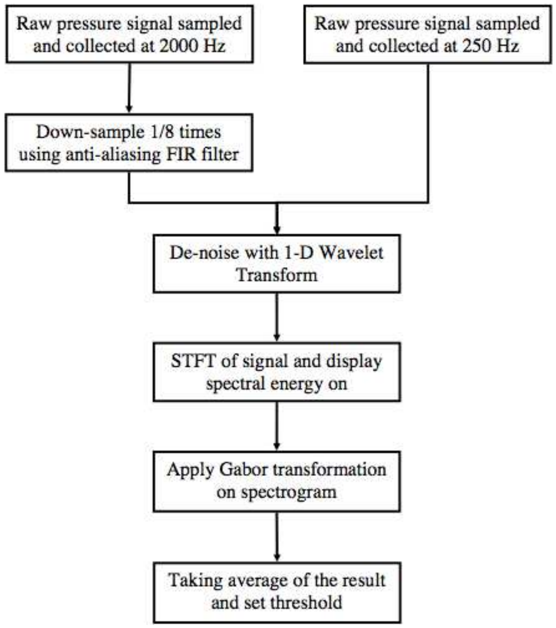

Fig. 4. Procedural Flow of the Frequency Domain Leak Detection Algorithm

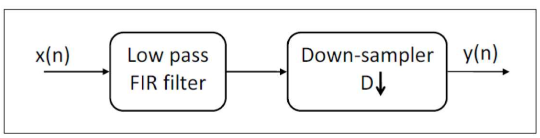

Fig. 5. Low pass FIR filtering follows by down-sampling. x(n) is the filter input sequence and y(n) is the filter output.

rate (250 Hz) is adequate. Therefore, the data are sampled and collected at 2kHz until the end of 2010 and 250Hz since then. Every 30 seconds, the sensor data are transmitted to a central server where different event detection algorithms are applied to identify the presence of anomalies in the signal. The detailed procedure of collecting the pressure signal can be found in [34]. The proposed burst detection algorithm is applied to the data kept in the server. It employs JTFA to detect leaks and bursts. Figure. 4 shows a procedural representation of the proposed algorithm.

The raw pressure signals are acquired and sampled at 2 kHz. To improve the computational efficiency of the process, these signals are re-sampled from 2 kHz to 250 Hz using an anti-

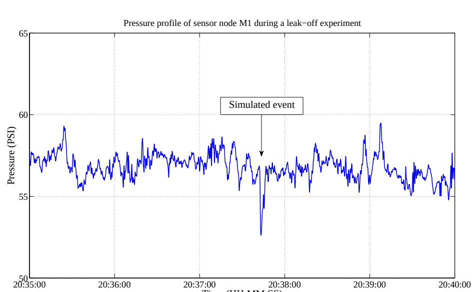

Fig. 6. Pressure traces collected at sensor node M1 during the leak-off experiment on WaterWiSe@SG test-bed

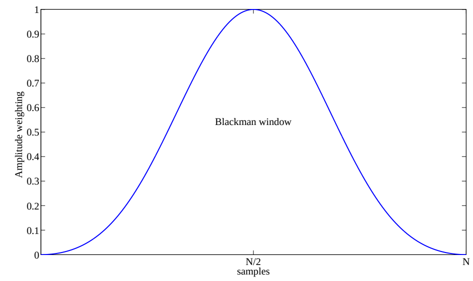

Fig. 7. Blackman window

aliasing (low pass) Finite Impulse Response (FIR) filter [35]. The process of down-sampling is shown in Figure. 5 and this process is not necessary for data acquired at 250 Hz. After that, a one-dimensional wavelet transform is applied to remove high frequency noise from the signal. Figure.6 shows the pressure transient signals after down-sampling and de-noising.

The next step is to identify the leak-induced features. Therefore, we use a spectrogram to extract those features. A spectrogram is the time varying spectral representation of the signal. It is computed using Short-time Fourier Transform (STFT). To accomplish this, the signal is divided into smaller chunks. When the Fourier transform of a block of data is computed, the resulting frequency spectrum suffers from spectral leakage, which is the generation of side lobes in the frequency spectrum. To correct this spectral leakage, an appropriate windowing function must be used. Therefore, the individual block of the signal is multiplied by a sequence of shifted Blackman window functions (Figure.7) in Equation 1 producing a sequence of time localized sub-signals.

$$\omega(n) = 0.42 + \frac{1}{2}cos\left(\frac{2\pi n}{N}\right) + 0.08cos\left(\frac{4\pi n}{N}\right) \quad ,0 \le n \le N \tag{1}$$

where N represents the window length, in samples, of the symmetrical Black- man window ω (n). To compensate for the ?loss? at the edges of the window, individual chunks may overlap in time.

After that, each sub-signal is transformed using the Short Time Fourier Transform in Equation 2 to obtain the time-varying spectral distribution of the signals. The STFT of the sub-signals is obtained by applying a 1024-point FFT to each sub-signal.

$$STFT[x(n)] = X(m,\omega) = \sum_{n=-\infty}^{\infty} x[n]\omega[n-m]e^{-j\omega n} \tag{2}$$

where x(n) is the signal to be transformed, and ω (n) is the Blackman window function (Equation 1).

$$\widehat{\sigma} = \sqrt{\frac{1}{N+1}\sum_{i=1}^{N+1}(x_i - x)^2} \tag{3}$$

According to Parseval's relationship of the Fourier Transform,

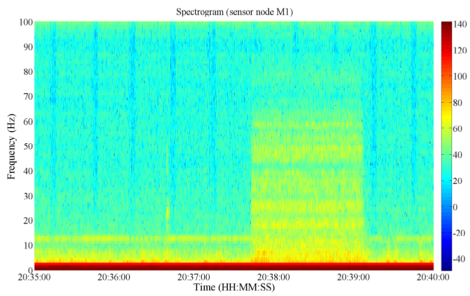

Fig. 8. Spectrogram of the simulated burst event during the leak-off experiment. The signal is collected from the sensor nodes which is 270 meters from the source. Spectrogram is created by taking the Short Time Fourier Transform in conjunction with the Blackman window function. X-axis indicates the time in HH:MM:SS and Y-axis indicates the frequency in Hz. The color of each point represents the intensity of spectral energy.

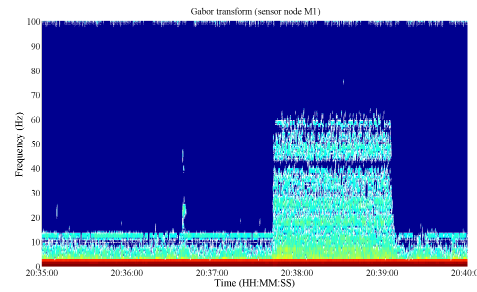

Fig. 9. After denoising using the Gabor transform. Spectrogram is denoised by applying Gabor transform in conjunction with the Blackman window function. X-axis indicates the time in HH:MM:SS and Y-axis indicates the frequency in Hertz. The color of each point represents the intensity.

the area under the energy spectral density curve is equal to the squared magnitude of the energy. Therefore, the spectrogram (Equation 4) of the signal can be estimated by computing the squared magnitude of the STFT of the signal.

$$Spectrogramx[t] \equiv |X(\tau, \omega)|^2 \tag{4}$$

The resultant spectral density is displayed on the spectrogram. Figure. 8 depicts the spectrogram of the pressure transients during a set of a controlled leak-off experiment where the horizontal axis represents time, and the vertical axis is frequency. The color of each point indicates the amplitude of a particular frequency at a particular time. Due to the symmetric property of the Fourier transform, only the first half of the spectrum is used to compute the spectrogram. As seen in Figure. 8, the noise tends to spread evenly over the entire joint time-frequency domain, and the signal energy is concentrated in the lower frequency band. Therefore, the Gabor transform with threshold T (Equation 5) is used as an adaptive filter to remove the unnecessary portion of the spectrogram. We used the Blackman-windowed Gabor transform to de-noise. To predict the noise components of the spectrogram, an estimate of the standard deviation $\widehat{\sigma}$ of the noise is calculated.

$$T = 0.55\widehat{\sigma}\sqrt{N \log N} \tag{5}$$

As seen in Figure. 8 and Figure. 9, the Gabor Transform simplifies the interpretation of the spectrogram, and the features representing the emulated bursts can be seen clearly. Afterthat, an optimum frequency range is selected to detect the leak-induced transients. The frequency range of 15-25Hz is selected because higher frequency suffers more attenuation, the lowest frequencies (1-3 Hz) are fundamental frequencies and frequencies within 4-15 Hz are composed of ambient noise of individual sensor node. Finally, a moving average function is applied to smooth the results (Figure. 10).

This technique has a trade-off between the spectral and temporal resolution. A wider Blackman window gives better

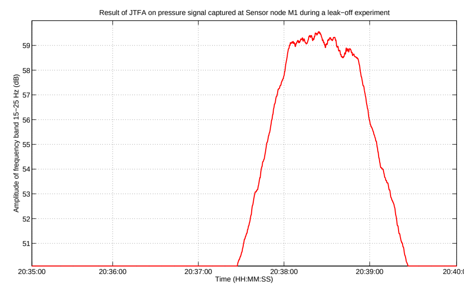

Fig. 10. Joint Time Frequency Analysis of simulated pressure transients on WaterWiSe@SG test-bed during the leak-off experiment. The signal is collected from the sensor nodes which is 270 meters from the leak

spectral resolution, whereas a narrower window gives improved temporal resolution.

IV. Energy Attenuation for Leak Localization

Leak localization is a fundamental issue of pipe failure monitoring using wireless sensor networks.

In this paper, we propose energy-based localization approach and exploit the strength of range-based approaches using JTFA. Ranging-based localization is an approach that identifies the positions of a leak in a network based on estimates of the distances between known measurement points and unknown leak.

When a wave travels through a junction of two or more pipes, part of the wave is reflected back. In a system without friction or tanks, transients could persist indefinitely. However, due to friction and loss of momentum in tanks, transients attenuate within seconds to minutes. This dispersion of the wave can be estimated using the transmission coefficient

$$s = \frac{\triangle H_s}{\triangle H_0} = \frac{2\frac{A_0}{a_0}}{\sum_{i=0}^{n}\frac{A_i}{a_i}} \tag{6}$$

, where s is dimensionless transmission factor, H_s and H_0 are head of transmitted and incident pulses, A_0 and a_0 are pipe area and wave-speed. The reflection coefficient may be obtained from Equation 7.

$$R = (s-1) = \frac{H_J - H_W}{H_W - H_0} \tag{7}$$

where H_0 is the initial head at the junction, H_J is the head at the junction after the wave has interacted with it and H_W is the magnitude of the initial wave.

In general, a leak-induced pressure wave can be described as a transient wave propagated from the leak along the pipeline in both upstream and downstream direction. During the leak, the transient wave is generated due to the changes of flow in the pipe. These transient phenomenon can be seen during the water distribution system operations such as opening and closing the valve and pump operations. The faster the operation the larger the magnitude of the transients. These are also known as water hammer phenomenon. In order to simulate the leak, a transient wave is simulated by maneuvering the valve in the pipe network.

In order to model the relationship of the intensity of pressure signal with the distance between sensor and the leak, the raw data were processed to obtain the intensity value for each of the frequency. The mean intensity value obtained at a given distance was calculated and variance and the standard deviation from the mean were determined. Then the intensity values are plotted against the distance and inverse relationship is verified. It is shown that the intensity and distance share an inverse relationship such that intensity decreases with the increases in distance. Then the linear regression is applied to generate a standard curve for each pipe diameter. After that, the intensity values from the real pipeline leakage are applied to approximate the distance between sensor nodes and the leak and to validate the relationship formulation. Once we obtain the distance matrix between detected sensors and leak, the sensors will be ranked according to their distance values. The nearest sensor will be ranked with the highest score. After that we indicate the distances from sensors along the pipeline. However, there could be more than one location with the same distance if the sensor node is connected to more than one pipe. In this case, we select the locations in the direction of the highest scored sensor as the candidate locations. The candidate location that satisfies all the distances from different sensors is identified as leak location. If more than one satisfy the conditions, the pipe section between then is chosen as the leak area.

As the characteristics of water transmission in the pipeline is guided transmission, the localization method used graph theory to search the most probable leak localization. Graphs can be conveniently represented as matrices, which is ideal for use with computers. Therefore, the graph is manipulated using the matrix computations.

To develop a matrix for a simple graph:

1) A square matrix is developed with vertices as both rows and columns (vertices in the same order).
2) If two vertices are joined together the number of edges joining them is entered in the matrix, if they are not joined by an edge then 0 is entered.
3) For simple graph, adjacency matrix uses zero-One representation of edges
4) In other words, for an adjacency matrix A = $[a_ij]$,
5) a_ij = 1 if i, j represents an edge of the graph a_ij = 0 otherwise.
6) For any undirected graph, the matrix is symmetrical

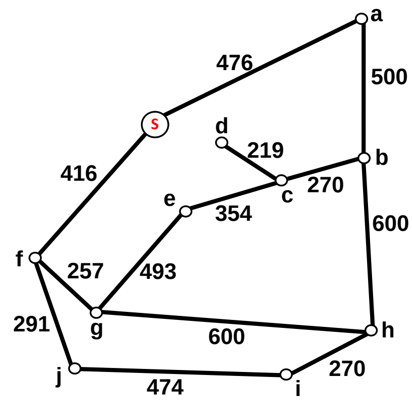

Fig. 11. The graphical representation of the network. S is chosen as the starting vertex.

The section of the network containing all the detected sensor nodes is represented with a weighted graph. Sensor nodes and junctions are represented with vertices and the connecting pipes with edges. The distance between the nodes are represented with weight.

Let v_i and v_j be the numbered vertices for $1 \leq i, j \leq N$ (N is the number of vertices).

Let w_ij be the weight of edge if there existe an edge e = $(v_i$,$v_j)$, $w_ij \geq 0$.

Let $M[i, j]$ be an adjacency matrix where M[i,j]=w_ij if there exists an edge $e = (v_i, v_j)$.

For each vertex i in the graph, $M[i, j] = 0$ and where no path exists, $M[i, j] = \infty$. Johnson's algorithm is used to find the shortest paths.

1) Johnson's algorithm: Johnson's algorithm works by using the BellmanFord algorithm to compute a transformation of the input graph that removes all negative weights, allowing Dijkstra's algorithm to be used on the transformed graph. This algorithm has a time complexity of O(n*log(n)+n*e), where n and e are number of nodes and edges respectively. It is named after Donald B. Johnson, who first published the technique in 1977.

Johnson's algorithm consists of the following steps.

This is useful when the shortest distance between any given node to any other node is to be found out. This method is useful to find out the route to transfer chemical, food products or manufacturing products from one point to another. It can also be useful to find out the shortest route between the distributor centre to the retailer stores.

In this case, this code uses distance estimates of the leak at multiple sensor nodes and attempts to determine the most probable pipe burst location.

11 shows the graphical representation of the network. A vertex S is chosen as starting point.

The location of the leak is searched with the minimization of the difference between the expected distances and the calculated distance from energy attenuation method. For each candidate nodes (measurement points and junctions), a score is calculated using 8.

$$score = \sum_{i=1}^{k-1} \sum_{j=2}^{k} \left| \omega_{M_{ij}} - \omega_{T_{ij}} \right|, \quad \forall \epsilon [1, N] \tag{8}$$

TABLE I
PSEUDOCODE OF JOHNSON'S ALGORITHM

Algorithm 1 Johnson's Algorithm

JOHNSON(G)

Compute G', where V[G'] = V[G] U $\{s\}$,
  E[G'] = E[G] U $\{(s, v) : v \in V[G]\}$, and
  $\omega(s, v)$ = 0 for all $v \in$ V[G]
if BELLMAN-FORD(G',ω, s) = FALSE
  then print "the input graph contains a negative-weight cycle"
  else for each vertex $v \in$ V[G']
    do set $h(v)$ to the value of $\delta(s, v)$
      computerd by the Bellman-FOrd algorithm
   for each edge $(u, v) \in$ E[G']
    do $\hat{\omega}(u, v) \longleftarrow \omega(u, v) + h(u) - h(v)$
   for each vertex $u \in V[G]$
    do run DIJKSTRA $(G, \hat{\omega}, u)$ to compute $\hat{\delta}(u, v)$ for all $v \in V[G]$
     for each vertex $v \in V[G]$
      do $d_u v \longleftarrow \hat{\delta}(u, v) + h(v) - h(u)$
   return D

Node with the minimum score is selected as the nearest node to the burst event. If two or more nodes have identical scores which is also the minimum score, then the burst location will be on the edge connecting those two nodes. After that, the search is refined to find the leak location on the pipe sections connecting to the nearest node. The virtual nodes are added along pipe section with equally spaced. Dijkstra's algorithm is used to re-compute shortest distance matrix and scores at each of the new nodes inserted in the graph are computed using 8. The node with minimum score is chosen as the most probable location of the leak.

V. LEAK-OFF EXPERIMENT

A number of techniques have been exploited to create and capture pressure transients to detect the presence of leaks. We have carried out a series of leak-off experiments to test the feasibility of the leak detection algorithm and to calibrate it accordingly. The in situ leak-off experiment is carried out on our WaterWise@SG test-bed.

In this section, we present the experimental validation of the Joint Time Frequency Domain Analysis approach for pipeline leak detection. The presence of leaks within the pipe imposes peaks on the spectrogram. Therefore, the peaks can be used as an indicator of the leaks.

The proposed methodology is verified with emulated leak-off experiments through the use of the WaterWiSe@SG test-bed. The experiments were performed within the operational water distribution system. Figure. 12 shows the local pipe network, covering an area of approximately $1km^2$ where the experiments were performed. These tests were carried out to verify the sensitivity of the pressure sensors for detecting leaks from afar, as well as the applicability of the leak detection algorithm on a real water distribution network. The leak-off experiment was carried out from 20:00 to 22:00 hours on March 16, 2010. The transients of the bursts were created using a solenoid valve attached to a fire hydrant. There were

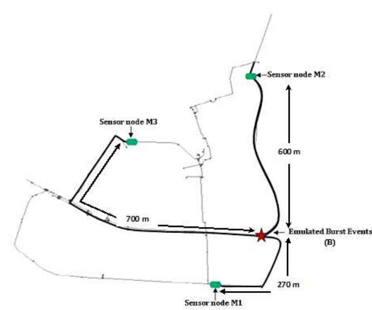

Fig. 12. Network layout for a portion of the WDS. Sensor nodes M1, M2 and M3 are the three measurement points and B is actual location of the burst events.

Fig. 13. Fire Hydrant that is used to create simulated bursts during the leak-off experiment

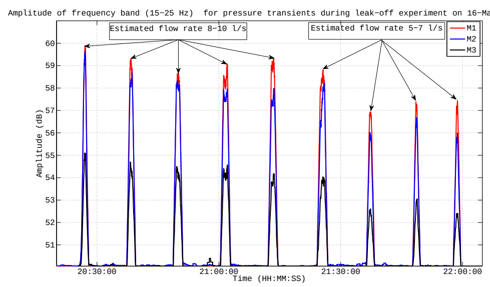

Fig. 14. Experimental results of the simulated burst events at sensor node M1, M2 and M3 where M1,M2 and M3 are located 270 m, 580 m and 700 m from the source respectively.

two flow rates created during experimentation, 8-10 l/s and 5-7 l/s. The first four bursts were generated at 8-10 l/s while the rest at 5-7 l/s. To create the transient, a solenoid valve was attached to one end of the hydrant, as shown in Figure. 13 while a globe valve was used to control the discharge rate of the bursts. When the solenoid valve was triggered to open, the water flowed out of the hydrant. As a result, a pressure transient wave was generated and propagated along the pipe. These pressure transients were acquired with the pressure transducers connected to the water distribution pipes. The sensor nodes sampled and collected these signals at 2 kHz. These signals were then transmitted to the central server for leak detection and localization processes and archived for future reference. A total of nine events with two different flow rates were created during this experiment. The pipe network for the test-bed covered an area of $1km^2$ and consisted of 500 mm steel and 300 mm ductile iron pipes with estimated wave speeds of 1030.3 ms^{-1} and 1088.7 ms^{-1}, respectively. Bursts were simulated at location B, and the three sensor nodes M1, M2, and M3 within range acquired pressure transient signals from the tests.

A. Results

Figure. 14 shows that all nine experimental burst events were detected at each of the three sensor nodes. Table II shows a summary of the outcomes of the analysis of the pressure data during the leak-off experiment on March 16, 2010, for measurement points M1, M2 and M3. These measurement points were selected to analyze the data because they had the closest proximity to the simulated bursts. As observed in Table 1, all three sensor nodes (within $1km^2$ of the emulated burst source) were able to detect all nine emulated bursts. Moreover, there were no false detections, i.e., detecting the events that were not created. These results demonstrate that the proposed technique can be used to detect leaks and bursts within a WDS.

As seen from the results (Figure. 14) of the leak-off experiment, the leak signals exist at a frequency below 200 Hz. We were encouraged to analyze the signal to reduce the sampling frequency without affecting the leak detection process. We did an assessment on sampling rate conversion using multi-scale wavelets and time difference of arrival for localization. We were convinced that we could achieve this at a sampling rate of 250 Hz. Therefore, we modified our sampling rate from 2 kHz to 250 Hz. The frequency resolution (Equation 9) of the spectrogram is coupled with the sampling rate and the number of FFT points. We also modified the algorithm in accordance with changed sampling frequency.

TABLE II
RESULTS OF JTFA ALGORITHM APPLIED ON EXPERIMENTAL PRESSURE PROFILE AT MEASUREMENT POINT M1,M2 AND M3

	Measurement Point (M1)	Measurement Point (M2)	Measurement Point (M3)
Total Number of Created Bursts	9	9	9
Total Number of Detected Bursts	9(100%)	9(100%)	9(100%)
Total Number of False Events	0(0%)	0(0%)	0(0%)
Total Number of Missed Events	0(0%)	0(0%)	0(0%)

$$FrequencyResolution = \frac{SampleRate}{no.FFTpoints} \tag{9}$$

VI. APPLICATION OF LOCALIZATION ALGORITHM ON REAL PIPE FAILURES

In this section, the validation of the proposed leak localization techniques is described and the results are presented. In this paper, we estimate the distance between the leak and the measurement sensor nodes by applying two methodologies (TDOA and Energy Attenuation) and gave an illustrative example using real pipe breakage in live water distribution system in Singapore.

The techniques were tested with real pipe breakages on 800 mm diameter pipe in a live water distribution network. The leak crack occurred on a live water pipeline during distribution. The pipe was 800 mm in diameter and 50 to 1800 meters away from our sensor nodes. The pressure measurements were collected at a sampling frequency of 250 Hz.

The leak crack was perpendicular to the pipe, from the 9 o' clock to the 6 o' clock position. The leak-induced transients were picked up by many of our sensor nodes. M3, M4, M5, and M6 are the sensor nodes located within $2km^2$ of the source of the leakage. The sensors detected two subsequent pressure drops. The initial drop is rapid and the subsequent drop is less rapid but more significant. This signature reflects the actual pipe break (first pressure drop) and a reflection from the closed valve (second drop). To estimate the distance from the source of the pipeline leakage to the measurement sensor nodes, the intensity of frequency at 15-25 Hz are calculated and TDOAs are estimated using the proposed methods.

Table III shows TDOA estimations of the burst events at the four measurement points. As we have the knowledge of network topology of bursts location, the distances between adjoining nodes and leak are calculated.

These values are then fed into localization algorithm, the estimated burst location using TDOA is 107.15 meters from sensor node M5 which is 32.85 meters from actual leak location. Using EA, the estimated burst location is 120.35 meters from the sensor node M5, 19.65 meters from the burst location.

TABLE III
DISTANCE, TOA AND INTENSITY VALUE FOR NH1 LEAK

Sensor node ID	Distance from leak location (m)	Time of Arrival (day)	Intensity value (dB)
M5	121	0.697242	85.966070
M3	1098	0.697255	76.660764
M4	1587	0.697258	68.688850
M6	1605	0.697263	64.596517

The second event KR1 results a sink hole. The leak was reported when the car was fallen into the sink hole. It happened 500-2000 meters from our deployed sensors. Three of our sensors detected the leak induced transient at 4:35 am.

The second event KR1 occurred on a 300 mm pipe. The leak transients were picked up by the sensor nodes M26, M12 and M31 which are 931 m, 1279 m, and 2357 m from the leak respectively.

Table IV shows distance estimations of burst events at measurement sensor nodes M26, M12 and M31. It is clear that the intensity sequence using energy attenuation technique is corresponding to the relative proximity of sensor nodes from the leak.

The most probable burst location using TDOA is 860.24 meters from node M26 towards node M12 which is 70.76 meters from the actual leak location. Using EA, the estimated burst location is 890.46 meters from node M26 towards node M12 which is 40.54 meters from the actual leak location.

The third event LVD1 occurred on a small pipe connecting to a larger 800 mm diameter pipe. The leak transients were picked up by M25, M35, M30 and M11 which are 245 m, 1244 m, 1500 m and 1890 m from the leak respectively. Table V shows distance estimations of burst events at M25, M35, M30 and M11. It can be perceived that the intensity sequence corresponds to the distance sequence in a non-linear relationship.

When these values are fed into localization algorithm, the most probable burst location using TDOA is 180.56 meters from node M25 which is 63.98 meters from the actual leak location. Using EA, the estimated burst location is 198.82 meters from node M25 which is 45.72 meters from the actual leak location.

The latest leak BCH1 occurred on a small pipe connecting to a larger 800 mm diameter pipe in the late 2013. The leak transients were picked up by M30, M11, M16, M22, M29 and M25 which are 343.64 m, 747.92 m, 878.86 m, 1367.61 m, 1483.58 m and 1667.45 m from the leak respectively. Table VI shows distance estimations of burst events at M30, M11, M16, M22, M29 and M25. It can be perceived that the intensity sequence corresponds to the distance sequence in a non-linear relationship.

The most probable burst location using TDOA is 410.24 meters from node 30 which is 66.6 meters from the actual leak location. Using EA, the estimated burst location is 382.46 meters from node 30 which is 38.82 meters from the actual leak location.

According to Table III, IV, V, VI and VII , energy attenuation technique for distance estimation has a clear advantage over TDOA estimation.

VII. CONCLUSIONS AND FUTURE WORKS

Pipe failures and leakages could be expensive for multiple reasons, including the loss of water, the cost and energy for generating and treating the water, deteriorating the water quality due to foreign particles intrusion and repaired cost. Moreover, the risk for public safety and surrounding infrastructure damage is also important for water authority.

This paper has presented an algorithm for identifying leaks and bursts within the water distribution network. The benefits of this method, com- pared to conventional time-domain methods (such as ITA [1] and WT [2]), are its simplicity and its ability to provide more robust anomaly identification. Moreover, the performance of the proposed method is less dependent on the characteristics of the water distribution system. As proof of the viability of the concept, our method has been validated through emulated bursts on the WaterWiSe@SG [3] test-bed.

In contrast to ITA, our technique does not require a pre-calibrated water distribution system model, and it is a fast and inexpensive technique that has been tested and successfully applied to a real water distribution system in Singapore. As shown by the results of both the experiments and the real leakage phenomenon, our JTFA method is capable of successfully identifying leaks.

To improve the detectability of the burst detection algorithm, the use of a dynamic threshold will be integrated. In addition, to obtain the most effective method, the proper integration of different leak detection techniques will be incorporated to complement the limitations of one another. Therefore, our future work will focus on a hybrid approach that enables the automatic detection and categorization of leaks/bursts within the water distribution network and approximates the location of these events.

Asset management is one of the important factors for the sustainable water infrastructure. It is especially important in urban areas to quickly detect and locate the leak to reduce the cost as well as the damage to the surrounding infrastructure.

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TABLE IV
DISTANCE, TOA AND INTENSITY VALUE FOR KR1 LEAK

Sensor node ID	Distance from leak location (m)	Time of Arrival (day)	Intensity value (dB)
M26	931.44	0.266939	78.741783
M12	1278.55	0.266947	69.762272
M31	2357.06	0.266292	61.052234

TABLE V
DISTANCE, TOA AND INTENSITY VALUE FOR LVD1 LEAK

Sensor node ID	Distance from leak location (m)	Time of Arrival (day)	Intensity value (dB)
M25	244.54	0.140300	84.634017
M35	1243.50	0.140347	64.700863
M30	1499.82	0.140322	62.190480
M11	1889.55	0.140319	61.612207

TABLE VI
DISTANCE, TOA AND INTENSITY VALUE FOR BCH1 LEAK

Sensor node ID	Distance from leak location (m)	Time of Arrival (day)	Intensity value (dB)
M30	343.64	0.185765	78.744699
M11	747.92	0.185777	61.427296
M16	878.86	0.185772	60.421389
M22	1367.61	0.185786	53.355037
M29	1483.58	0.185782	53.334393
M25	1667.45	0.185777	53.248735

TABLE VII
SUMMARY OF LOCALIZATION PERFORMANCE

Event ID	Distance from actual location using TDOA (m)	Distance from actual location using EA (m)
NH1	32.85	19.65
KR1	70.76	40.54
LVD1	63.98	45.72
BCH1	66.6	38.82

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REFERENCES

[1] D. Covas, A. Jacob, H. Ramos, Bottom-up analysis for assessing water losses: A case study, in: Water Distribution Systems Analysis Symposium 2006, ASCE, 2006, pp. 1–19.

[2] P. J. Lee, M. F. Lambert, A. R. Simpson, J. P. Vítkovskỳ, J. Liggett, Experimental verification of the frequency response method for pipeline leak detection, Journal of Hydraulic research 44 (5) (2006) 693–707.

[3] J. A. Liggett, L.-C. Chen, Inverse transient analysis in pipe networks, Journal of Hydraulic Engineering 120 (8) (1994) 934–955.

[4] I. N. Ferraz, A. C. Garcia, F. C. Bernardini, Artificial neural networks ensemble used for pipeline leak detection systems, ASME, 2008.

[5] J. Mashford, D. De Silva, D. Marney, S. Burn, An approach to leak detection in pipe networks using analysis of monitored pressure values by support vector machine, in: Network and System Security, 2009. NSS '09. Third International Conference on, 2009, pp. 534–539.

[6] D. Covas, H. Ramos, Hydraulic transients used for leakage detection in water distribution systems, in: Proc. 4th Intl. Conf. Water Pipeline Systems York UK, 2001, pp. 227–241.

[7] D. Covas, H. Ramos, Case studies of leak detection and location in water pipe systems by inverse transient analysis, Journal of Water Resources Planning and Management 136 (2) (2010) 248–257.

[8] J. P. Vítkovskỳ, M. F. Lambert, A. R. Simpson, J. A. Liggett, Experimental observation and analysis of inverse transients for pipeline leak detection, Journal of Water Resources Planning and Management 133 (6) (2007) 519–530.

[9] O. Hunaidi, W. T. Chu, Acoustical characteristics of leak signals in plastic water distribution pipes, Applied Acoustics 58 (3) (1999) 235–254.

[10] O. Hunaidi, W. Chu, A. Wang, W. Guan, Detecting leaks, JOURNAL AWWA 92 (2) (2000) 82–94.

[11] I. Stoianov, L. Nachman, S. Madden, T. Tokmouline, M. Csail, Pipenet: A wireless sensor network for pipeline monitoring, in: Information Processing in Sensor Networks, 2007. IPSN 2007. 6th International Symposium on, IEEE, 2007, pp. 264–273.

[12] A. J. Whittle, L. Girod, A. Preis, M. Allen, H. B. Lim, M. Iqbal, S. Srirangarajan, C. Fu, K. J. Wong, D. Goldsmith, Waterwise@ sg: A testbed for continuous monitoring of the water distribution system in singapore, Water Distribution System Analysis, WSDA.

[13] S. Beck, M. Curren, N. Sims, R. Stanway, Pipeline network features and leak detection by cross-correlation analysis of reflected waves, Journal of hydraulic engineering 131 (8) (2005) 715–723.

[14] S. M. Taghvaei, Fast leak detection and location of water pipelines based using orthogonal wavelet transform, in: ICPTT 2009@ sAdvances and Experiences with Pipelines and Trenchless Technology for Water, Sewer, Gas, and Oil Applications, ASCE, 2009, pp. 186–192.

[15] S. Srirangarajan, M. Allen, A. Preis, M. Iqbal, H. B. Lim, A. J. Whittle, Water main burst event detection and localization, in: Proc. 12th Water

Distribution Systems Analysis Conference (WDSA), 2010.
[16] P. J. Lee, J. P. Vítkovskỳ, M. F. Lambert, A. R. Simpson, J. A. Liggett, Frequency domain analysis for detecting pipeline leaks, Journal of Hydraulic Engineering 131 (7) (2005) 596–604.
[17] W. Mpesha, S. L. Gassman, M. H. Chaudhry, Leak detection in pipes by frequency response method, Journal of Hydraulic Engineering 127 (2) (2001) 134–147.
[18] W. Mpesha, M. Hanif Chaudhry, S. L. Gassman, Leak detection in pipes by frequency response method using a step excitation, Journal of hydraulic research 40 (1) (2002) 55–62.
[19] T. T. T. Zan, K.-J. Wong, H. B. Lim, A. J. Whittle, A frequency domain burst detection technique for water distribution systems, in: Sensors, 2011 IEEE, IEEE, 2011, pp. 1870–1873.
[20] M. Taghvaei, S. Beck, W. Staszewski, Leak detection in pipelines using cepstrum analysis, Measurement Science and Technology 17 (2) (2006) 367.
[21] R. S. Pudar, J. A. Liggett, Leaks in pipe networks, Journal of Hydraulic Engineering 118 (7) (1992) 1031–1046.
[22] J. P. Vítkovskỳ, A. R. Simpson, M. F. Lambert, Leak detection and calibration using transients and genetic algorithms, Journal of Water Resources Planning and Management 126 (4) (2000) 262–265.
[23] D. Misiunas, J. Vitkovsky, G. Olsson, M. Lambert, A. Simpson, Failure monitoring in water distribution networks, Water science and technology 53 (4-5) (2006) 503–511.
[24] D. Misiunas, M. Lambert, A. Simpson, G. Olsson, Assessing water mains condition using hydraulic transients, Proceedings of the ICE-Water Management 160 (2) (2007) 89–94.
[25] P. J. Lee, J. P. Vítkovskỳ, M. F. Lambert, A. R. Simpson, J. Liggett, Leak location in pipelines using the impulse response function, Journal of Hydraulic Research 45 (5) (2007) 643–652.
[26] M. Ferrante, B. Brunone, Pipe system diagnosis and leak detection by unsteady-state tests. 1. harmonic analysis, Advances in Water Resources 26 (1) (2003) 95–105.
[27] M. Ferrante, B. Brunone, S. Meniconi, Wavelets for the analysis of transient pressure signals for leak detection, Journal of Hydraulic Engineering 133 (11) (2007) 1274–1282.
[28] X.-l. GUO, K.-l. YANG, Y.-x. GUO, Hydraulic pressure signal denoising using threshold self-learning wavelet algorithm, Journal of Hydrodynamics, Ser. B 20 (4) (2008) 433–439.
[29] X. Tang, Y. Liu, L. Zheng, C. Ma, H. Wang, Leak detection of water pipeline using wavelet transform method, in: Environmental Science and Information Application Technology, 2009. ESIAT 2009. International Conference on, Vol. 2, IEEE, 2009, pp. 217–220.
[30] S. Srirangarajan, M. Allen, A. Preis, M. Iqbal, H. B. Lim, A. J. Whittle, Wavelet-based burst event detection and localization in water distribution systems, Journal of Signal Processing Systems (2011) 1–16.
[31] S. Qian, D. Chen, Joint time-frequency analysis: methods and applications, Prentice-Hall, Inc., 1996.
[32] J. S. Walker, Y.-J. Chen, Denoising gabor transforms, Preprint available at http://www. uwec. edu/walkerjs.
[33] S. W. Smith, et al., The scientist and engineer's guide to digital signal processing.
[34] M. Allen, A. Preis, M. Iqbal, S. Srirangarajan, H. B. Lim, L. Girod, A. J. Whittle, Real-time in-network distribution system monitoring to improve operational efficiency, Journal American Water Works Association (AWWA) 103 (7) (2011) 63–75.
[35] J. G. Proakis, Digital signal processing: principles algorithms and applications, Pearson Education India, 2001.
[36] A. J. Whittle, M. Allen, A. Preis, M. Iqbal, Sensor networks for monitoring and control of water distribution systems,The 6th International Conference on Structural Health Monitoring of Intelligent Infrastructure, 2013.

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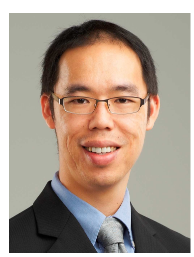

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