Abstract In this paper we present techniques for detecting and locating transient pipe burst events in water distribution systems. The proposed method uses multiscale wavelet analysis of high rate pressure data recorded to detect transient events. Both wavelet coefficients and Lipschitz exponents provide additional information about the nature of the signal feature detected and can be used for feature classification. A local search method is proposed to estimate accurately the arrival time of the pressure transient associated with a pipe burst event. We also propose a graph-based localization algorithm which uses the arrival times of the pressure transient at different measurement points within the water distribution system to determine the actual location (or source) of the pipe burst. The detection and localization performance of these algorithms is validated through leak-off experiments performed on the WaterWiSe@SG wireless sensor network test bed, deployed on the drinking water distribution system in Singapore. Based on these experiments, the average localization error is 37.5 m. We also present a systematic analysis of the sources of localization error and show that even with significant errors in wave speed estimation and time synchronization the localization error is around 56 m.

Keywords Multiscale wavelet analysis · Transient detection · Pipe burst · Burst localization

1 Introduction

Water distribution infrastructure in cities around the world is rapidly aging and experiencing failures with increasing frequency. In the United States, there are an estimated 237,600 pipe breaks per year [2]. As the population in cities grows, the demand on these critical infrastructures also grows. Utility operators around the world are faced with increasing costs of laying new pipes (to serve the growing population) as well as maintaining and replacing aging pipes. In addition, increases in pumping, treatment and operational costs are pushing water utilities to combat water loss by developing methods to detect, locate and correct leaks. In the United States, an estimated 7,000 km of pipe requires replacement each year at a cost of around $2.7 billion and the water losses, estimated to be 10 %, cost around $4.3 billion per year [2]. \footnote{Cost figures from [2] have been adjusted for inflation.} It is also worth noting that countries such as England, France and Italy have water losses in the 20–30 % range [1]. Thus, real-time monitoring and maintenance of water distribution
system (WDS) infrastructure is becoming vital to ensure efficient, reliable operation and timely response to infrastructure failure.

Wireless sensing technology has advanced to the point that the deployment of dense networks of low-cost devices for real-time infrastructure monitoring is now feasible. When combined with appropriate data processing techniques, the increased density and availability of these measurements enables improved response, management and prediction of infrastructure failures.

For water utility operators, the ability to detect and localize pipe bursts and leaks quickly is important. Sudden pipe bursts can occur in high-pressure water transmission mains and distribution pipelines. Bursts can be very expensive due to the outage time while the damaged pipe is repaired, the cost of repair, and damage to surrounding property and facilities. In addition, such failures can have significant social (e.g. service interruptions, traffic delays, etc.) and environmental (e.g. lost water and energy) impacts [5]. As a result, it is advantageous to minimize the detection and location time after the burst event occurs. Since the pipes in a water distribution network are pressurized, many burst events can be detected as transients against the background pressure levels in the WDS [9]. In civil engineering, transient refers to a pressure wave that is short lived.

In this paper we present a technique for detecting and localizing events in a WDS based on pressure traces gathered by a dense wireless sensor network (WSN). Our event detection technique uses wavelet-based multiscale analysis of the pressure signal to detect transients. Due to the impulsive nature of noise present in the pressure transients, the first step in this analysis is to apply wavelet de-noising. We then obtain wavelet decomposition of the de-noised signal. The wavelet coefficients are used to identify features at a range of scales. We then apply temporal consistency rule across scales to differentiate between coherent signal features and noise. The next step uses the wavelet coefficients and the Lipschitz exponent to obtain additional information about the nature of the signal which is used for feature classification. If a burst transient event is detected, the multiscale analysis is combined with a focusing algorithm to estimate accurately the arrival time of the burst transient. The focusing algorithm determines the arrival time of the pressure transient at the measurement points starting from a rough estimate.

For localization, we present a graph-based search algorithm which uses the arrival times of the transient at the measurement points to localize the event. This search algorithm is split into a coarse global search and a fine local search.

Our contributions are as follows:
1. The identification and application of appropriate event detection techniques to high-rate pressure data;
2. The design and implementation of novel event detection and localization algorithms and integration into a dataflow for on-line operation;
3. The evaluation of the proposed event detection and localization algorithms on realistic data traces gathered from in-situ experimentation;
4. The systematic analysis of sources of error in the results.

The rest of this paper is organized as follows: Section 2 provides some background on monitoring systems, transient events and existing event detection/localization techniques, with specific reference to WDS. Section 3 presents our wavelet-based event detection scheme and Section 4 presents our graph-based localization algorithm. Section 5 describes the experimental set-up and presents the performance evaluation of the detection and localization techniques. In Section 6, we identify the sources of localization error and present a systematic analysis of their impact on localization performance. Finally, Sections 7 and 8 draw conclusions and identify areas for future work.

2 Background

Currently, water utilities use a variety of telemetry solutions that are integrated into a supervisory control and data acquisition (SCADA) system for monitoring the WDS. However, such systems are expensive limiting them to a few critical points and only serve low data rate applications. There is a growing need for monitoring solutions that can be deployed at lower cost while providing data with higher spatial and temporal resolution.

There have been recent efforts at developing a WDS monitoring system. PipeNet, a system based on WSN for monitoring large-diameter bulk transmission pipelines, included field deployment of a small network for 22 months [27, 28]. However, much of the analysis and experimentation was carried out off line and in laboratory settings. In addition, the PipeNet authors used a relatively limited sensing platform (Intel mote) to optimize for power consumption, which limited their sampling regime (100 Hz for five seconds at five minute intervals). WaterWiSe@SG represents a significant ad-
vancement over these systems by providing real-time measurements at higher data rates and enabling in situ experimentation [3].

In a WDS, typical events of interest to detect include leaks, pipe bursts and planned system operations (such as valve closures). Most of these events can be detected as transients in pressure within the WDS. Slow leaks, valve and other maintenance operations typically result in transients that can be detected over a time scale of minutes or hours. On the other hand, pipe burst events result in a pressure transient which must be detected over time scale from milliseconds to seconds [29].

Pipe breaks and bursts occur in pressurized water pipes over time due to the cumulative effects of corrosion, structural fatigue due to fluctuations of fluid pressure or environmental factors causing movements in the supporting soil mass. As pipes age, they become increasingly susceptible to bursts and leaks [23]. Pipe burst events result in a sudden change in the flow through the pipe producing a pressure transient which propagates along the pipeline. This pressure pulse travels in both directions away from the burst origin at the speed of sound in water (wave speed of the pipe) [20].

The pulse is reflected by pipe junctions and endpoints in the physical network, and its speed is altered by the pipe material and diameter as it travels through the network [15]. The transient is also attenuated by friction in the pipes, causing dispersion that reduces the slope or steepness of the transient wavefront [6, 7]. The pressure transient, when detected at a number of measurement points can provide information on the location of the burst.

The burst (and subsequent leak) also create distinct acoustic emissions, changing the background acoustic signature of the pipe [3]. There is significant literature and established practice for determining accurately the location of existing leaks using the cross correlation of ground-level (microphone) or insertion-based acoustic measurements (hydrophone) [8, 14]. However, in order to detect and localize instantaneous burst events (and hence give a starting point to accurately locate the leak), it is advantageous to use pressure measurements. This is because acoustic signal attenuation increases with frequency and the frequency of acoustic emissions can range well into the kilohertz depending on factors such as pipe material/size and soil type. In addition, the lower frequencies are significantly affected by environmental noise, such as that from vehicles and pumps. Thus, passive acoustic detection techniques are effective only within few tens of meters of the leak [17]. On the other hand, pressure transients are less readily attenuated and the pressure signature is relatively unaffected by background noise than acoustic emissions, increasing the distance over which they can be reliably detected [25].

A common way to detect a transient in additive noise is to filter the signal, then compare the output to a threshold, and declare each threshold crossing as an arrival of a transient. In addition, since in most real world signals, singularities do not occur at a single resolution, multiscale analysis is required. Multiscale analysis is directly related to wavelet analysis. In wavelet analysis, a one dimensional signal is mapped into a time-scale representation using a bank of bandpass filters. Wavelet analysis for singularity or transient detection has been used with many types of time-series data such as seismograms [32] or pulmonary microvascular pressure signals [16]. Wavelet analysis has also been proposed to detect transients in pressure signals for leak detection and location in water pipelines [26].

In the case of an ideal step edge, the position of the transition corresponds to the extremum of the response of the bandpass filter to the signal. This extremum propagates when the scale (frequency) parameter is changed. Such techniques perform well when dealing with isolated singularities. However, in the case of a noisy singularity, as generally encountered in most physical phenomena, the singularity can be detected only over a limited range of scale. In the case of two noisy close singularities for example, the simple scale by scale analysis will detect many wrong positions at fine scales corresponding to a response both to the noise input and to the singularities to be detected. At a coarser scale, only one event at an inaccurate position will be detected due to the blurring effect. This explains the need for an algorithm that extracts relations between features at different levels of scale and uses this to perform transient event detection.

Event detection in general is an elaborately studied research area [12]. The cumulative sum (CUSUM) test has been extensively applied for change detection in different time series analysis problems [4]. Misiunas et al. propose a method for detecting the pressure transient associated with a burst event using the CUSUM test [21]. In situations where the measurement data contains a high level of noise, they propose a noise pre-filtering using an adaptive Recursive Least Squares (RLS) filter. Techniques for detecting and locating pipe bursts in WDS using the negative pressure wave theory have also been studied in the literature. These attempt to detect bursts based on the low-pressure surge generated by pipe rupture. However, most of these techniques consider single pipelines and have not been applied to network systems [22, 24].
Another approach is to inject customized pressure signals into a pipeline and analyze the subsequent behavior of the transient. As it travels, the transient signal acquires properties that relate to the configuration and integrity of the system. Analysis of this signal can help expose and locate leaks. In [30], a methodology based on this was proposed which uses harmonic analysis of the system’s transient response for inference. Although the technique is simple to use and apply, the authors note that it is not generally applicable to pipe networks due to the complex waveforms created by complicated geometries such as branches and loops and demands, which may be difficult to distinguish from leaks.

Methods have been proposed for burst (or leak) localization. However very few have been proposed in the context of a large network. In addition, most have been validated using simulated data [22], in controlled laboratory environments [21, 26], or in transmission pipelines which are immune from pressure variations due to demand fluctuations [20]. To our knowledge this is the first instance of event detection and localization algorithms being validated on a real urban-area WDS.

Misiunas proposed a search-based burst localization technique [20]. In this technique, the search is first performed globally over all nodes in the network. In the (optional) second step, additional nodes are placed along each of the pipes, if the burst is inferred to have occurred along the pipe, and the global search procedure is repeated. The objective function in the search procedure consists of two parts: one based on the arrival times of the transients and the other based on the pressure wave magnitude at different points in the network. In the second step, for each pair of adjacent nodes, one additional node is placed along the connecting pipe. Since both steps of this algorithm perform a global search, a high density of nodes in the network is required to achieve good localization accuracy.

3 Wavelet-based Event Detection

Real-time monitoring of a WDS gives us the ability to detect events such as leaks, pipe bursts and system operations (such as valve opening/closure). Most of these events can be detected as transients in pressure within the WDS [29]. An outline of the proposed wavelet analysis based event detection scheme is shown in Fig. 1.

The data acquired by the pressure sensors can contain impulsive noise as well as signatures due to operational events, so the first step in the wavelet analysis is to preprocess the raw pressure signal. We apply wavelet de-noising to the raw pressure signal. The pressure signal is decomposed into approximation and detail coefficients. In the first few decomposition levels, extremes of the details are both due to noise and signal features. As the scale increases, noise extremes decay while extremes of the noise-free signal remain. Noise at each level is estimated based on the standard deviation of the detail coefficients and is used as threshold for the detail coefficients. The clipped details and approximation coefficients are used to reconstruct the de-noised signal which is used for detecting burst transients. The de-noised signal is decomposed into 4 levels for further analysis.

In the next step, we identify signal features by considering the detail coefficients at levels 3 and 4 ($d3$ and $d4$), since the extremes of the details up to level 2 were found to be the result of both noise and signal features. It has been shown that the detail coefficients associated with signal features are retained or enhanced over scales while those due to noise decay rapidly with scale [18]. The signal features are identified by looking at groups of detail coefficients with significant amplitude. The amplitude of the most significant coefficient in each group and the corresponding time index are recorded. Among these groups we compare the magnitude of the significant coefficients across scales. If the coefficient magnitudes are retained or enhanced as we move to higher levels, the feature (or group) is identified as a possible signal feature.

We next check the temporal consistency of each of the identified features across scales. However, since the signal is down-sampled as we go higher in the decomposition levels, a signal feature (such as a burst transient) which is represented by $m$ samples at level
detail, would be represented by only around $m/2$ samples at level $N$. Thus, the temporal spread of a feature ($\Delta t$) across $N$ levels of scale must satisfy the following condition:

$$\Delta t \leq 2^N \cdot T_s$$

where $T_s$ is the sampling period. This allows us to distinguish useful signal transitions from noise [19].

The wavelet coefficients provide additional information about the identified signal features which can be used for feature classification. It is well known that the local singularity of a signal can be described with the Lipschitz exponents [18]. The Lipschitz exponent ($\alpha$) of a signal feature, around time $t_{sf}$, can be approximated as [13]:

$$\alpha = \log_2 M_{j+1} - \log_2 M_j$$

where $M_j$ represents the local maxima of $|W_j(p_d(t_{sf}))|$, the wavelet transform modulus of the de-noised pressure signal $p_d$ around time $t_{sf}$ at scale $2^j$ ($W_j$ represents the wavelet transform). In addition, the sign of the extremum values of the detail coefficients indicate whether the edge is ascending or descending. When observed at the measurement points, a burst event produces a negative pressure drop, followed by reflections of the original transient from pipe junctions and endpoints, eventually returning to the baseline pressure in the pipe [20]. The magnitude and temporal spacing of the negative detail coefficients, representing the gradual rise in pressure as it returns to the baseline, allow us to identify burst transients. Fig. 2 illustrates the wavelet analysis for a typical pressure transient signature due to an emulated burst event.

Detecting the transient at a number of measurement points can provide enough information to determine the location of the burst. In order to localize the burst event, we must accurately estimate the arrival time of the burst transient at each of the measurement points. It is shown, in Fig. 2, that extremum of the detail

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**Figure 2** Multiscale wavelet analysis: Identifying signal features. *Top plot* shows the denoised pressure signal and the *lower four plots* show the detail coefficients ($d1$–$d4$) following a 4-level wavelet decomposition.
coefficients at level 4 determines the approximate position of the transient. We then start from this level and move to lower levels to improve the arrival time estimate of the transient since its position is affected after each low pass filtering operation. The initial coarse time estimate is used to perform detection at the lower scale level (or finer resolution) in a thin region around the previous position, giving the most accurate estimate of the arrival time.

4 Graph-based Search Algorithm for Burst Localization

When we have several arrival time estimates of the same burst event, the observations can be fused to provide an estimate of the burst location within a search space. Since the burst location is constrained, i.e. it must lie somewhere on a pipe within the boundaries of the pipe network, we must first define an appropriate representation for the network in order to define the search space. The following definitions allow us to model the pipe network as a graph (refer to Fig. 3 for a visualization):

- **Nodes**: pipe junctions, endpoints and measurement points (or deployed pressure sensor locations),
- **Edges**: pipe sections which connect the nodes,
- **Edge weights**: travel time ($\tau_p$) for the edge (or pipe section), $\tau_p = L_p/C_p$ where $L_p$ is the length of the pipe section and $C_p$ is the wave speed.

Using the graph model, we propose to determine the burst location using the difference in the arrival times of the burst transient at the measurement points.

**Figure 3** Pipe network layout and the equivalent graph model for a portion of the WDS. M1, M2 and M3 are the three measurement points (sensors) and B is actual location of the burst events. The expected travel paths from B to the three measurement points are shown in solid lines. The dashed path indicates a possible second path from B to M3.
in the WDS. In order to localize a burst event using this approach, the burst transient has to be detected at two or more measurement points. We assume that the measurement points are time synchronized and gather time tagged data.

We formulate the problem as follows: the burst event occurs at time $t_B$ which is not known a priori. If the burst transient is detected at nodes $j$ and $k$ at times $t_j$ and $t_k$, respectively, the travel times from the burst location to the measurement points $t_j - t_B$ and $t_k - t_B$ cannot be determined. However, since the measurements are time synchronized, the difference between the arrival times $t_j - t_k$ is known. Also, since the pressure transient will only travel a finite distance (a few hundred meters depending on the pipe network) before being fully damped, it will be detected only in a small sub-network of the WDS. Thus, it is likely that this arrival time difference is unique for bursts occurring at different points in the network.

Assuming the pipe parameters and wave speeds are known, it is possible to calculate the shortest travel time between any two nodes in the system, for example using Dijkstra’s algorithm [10]. Let $\tau_{ik}$ represent the travel time from node $j$ to $k$. If the burst occurs at node $i$, where $i = 1, \ldots, N$ ($N$ is the number of nodes in the network) then:

$$\sum_{i \neq k} |(t_j - t_k) - (\tau_{ij} - \tau_{ik})| = 0. \quad (3)$$

However, due to timing, measurement and other errors, the left-hand side of Eq. 3 will never be zero. Thus, to identify the burst location, a search algorithm is proposed. The search is divided into two steps:

- **Step 1: Search for the node nearest to the burst location**
  In this step, we assume that the burst event occurred at one of the nodes in the network. Based on Eq. 3, for each node $i$ in the network we compute a score (or error metric) $s_i$ given by:

$$s_i = \sum_{j \in S_B} |(t_j - t_k) - (\tau_{ij} - \tau_{ik})| \quad (4)$$

where $S_B$ is the set of measurement points (or sensors) that detected the burst transient. Smaller residual value $s_i$ indicates higher probability that the burst occurred at node $i$. Thus, the node with the minimum score is selected as the node nearest to the burst location, which we denote as node $n_B$.

- **Step 2: Search for the burst location along pipe sections connected to the nearest node**
  In this step, a new set of virtual nodes is placed along the pipe sections (i.e., along the edges in the graph model) connected to the node $n_B$ determined from Step 1. This amounts to a local search around the node estimated to be closest to the burst location. The new nodes are placed using a distance step-size which is dependent on the time resolution of the pressure data (i.e., sampling period $T_s$) and wave speed in the pipe section. The shortest travel times from the new set of nodes to the measurement points are recalculated and used to compute the scores (Eq. 4). Finally, the node with the minimum score is chosen as the most probable burst location.

The first step of the search algorithm for burst localization described above performs a coarse global search over all nodes in the network. The second step performs a local search around the nearest node estimate to determine the most probable burst location along the pipe section.

## 5 Experimentation and Results

The performance of the proposed event detection and localization algorithms is verified through leak-off experiments performed on the WaterWiSe@SG test bed deployed on the WDS in Singapore [3, 31]. WaterWiSe@SG is an integrated, end-to-end system dealing with node-level acquisition and transmission of data as well as server-based archiving, processing, and visualization of data. The test bed consists of sensor nodes measuring hydraulic and water parameters in real-time, and transmitting the data to the archive server. The sensor node supports simultaneous attachment of a pressure transducer, a flowmeter, a hydrophone, and water quality sensors for pH and oxidation reduction potential (ORP). The nodes are equipped with a USB 3G modem for continuous wireless transmission of sensor data. The sensor nodes are synchronized to a common time frame using the Pulse Per Second (PPS) feature of their on-board GPS modules.

Pressure measurements are recorded at a sampling frequency of 250 Hz.² The 250 Hz pressure data is de-noised and used for detecting burst transients. In addition, the de-noised pressure signal is low-pass filtered and appropriately down-sampled for detecting longer

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²During the initial phase of the WaterWiSe@SG deployment, pressure was sampled at 2 kHz. Wavelet analysis of the burst transients revealed that the detail coefficients above 125 Hz did not aid in identifying the burst events. Thus, sampling frequency for pressure was reduced to 250 Hz.
time-scale transients (such as slow leaks and valve operations).

The leak-off experiments were performed using a 2-inch diameter solenoid-controlled valve, with a nominal opening time of 0.1 s, connected to the pipeline via an air valve or a fire hydrant. The solenoid-controlled valve is triggered to create transients emulating instantaneous pipe breaks. A globe valve was used to control the discharge rate. Fire hydrant plugs were used as connection points for the burst emulation equipment. The part of the distribution network where the bursts were created consists of 500 mm steel and 300 mm ductile iron pipes with estimated wave speeds of 1030.3 m/s and 1088.7 m/s, respectively. The pipe network layout for the test bed and the equivalent graph model are shown in Fig. 3, covering an area of around 1 km². The bursts were created at location B. Three of the measurement points (or pressure sensors) M1, M2 and M3, part of the WaterWiSe@SG test bed, were within range to be able to detect the burst transients. Nine burst events were created during the evening from 20:00 to 22:00 h. The discharge rate was 9 L/s for events 1–4, 7 L/s for event 5 and 5 L/s for events 6–9.

5.1 Detection Performance

The pressure data from the 2 h experimentation period was analyzed using the multiscale wavelet algorithm, implemented in Matlab. We employ the Daubechies db1 wavelet due to its compact support, symmetry, orthogonality and linear phase properties, useful for characterization of transients [11]. A 4-level decomposition was found to be a good fit for the pressure data being analyzed as detail coefficients above level-4 do not aid in identifying the burst transients. A typical pressure transient signature at the three measurement points from one of the emulated burst events is shown in Fig. 4.

As a point of comparison to existing approaches, we also implemented the CUSUM change detection test [21], shown in Eq. 5:

\[ S_0 = 0 \]
\[ S_t = \max (S_{t-1} - \epsilon_t - \nu, 0) \] if \( S_t > h \) then issue alarm and set \( t_a = t, S_t = 0 \)

![Figure 4](image-url) Pressure transient signature at the three measurement points from one of the emulated burst events.
where $S_0$ is the initial cumulative sum value, $S_t$ and $S_{t-1}$ are the cumulative sum values at the current and previous time steps, $h$ and $\nu$ are threshold and drift parameters, and $\epsilon_t$ is the residual between data samples $\theta_t$ and $\theta_{t-1}$. When $S_t$ reaches the threshold value $h$, the time of change $t_a$ is recorded.

It was noted in [20] that the CUSUM technique is susceptible to false positives, caused by non-burst pressure transients such as pump shutdowns, valve operations or sudden increases in demand. This is because the CUSUM test detects burst transients based only on the rate of change criterion and does not attempt to classify the transient signatures. The CUSUM test parameters were tuned such that all the emulated bursts were detected ($h = 2.92$ psi and $\nu = 0.0002$ psi). These parameters were kept constant across all nodes, and were chosen by analyzing the values of $S$ and $\epsilon$ for one minute of data around each burst event individually, finding values that ensured at least one positive detection for each event.

The detection results, for the 2 h period with 9 control events, using the above two methods are shown in Table 1. The detection performance is judged based on the following three metrics:

- **True detections**: Emulated burst events that were detected correctly.
- **False detections**: Detected transient events that were not part of the emulated burst events.
- **Missed events**: Emulated burst events that could not be detected.

The wavelet-based algorithm was able to detect all the 9 events at M1, M2 and M3, however there was one false detection at M1. Using the $h$ and $\nu$ parameters we chose, the CUSUM algorithm detected 38 false positives. In our analysis we were not able to find values for $h$ and $\nu$ that provided similar performance as the wavelet-based method. The difference in false detections between the techniques shows the limitation of relying solely on a change detection technique such as CUSUM for detection of specific types of events (such as pipe bursts), as all transient events meeting the change criteria will be considered meaningful. This implies that some further step of classification after detection is required. In our algorithm, the feature classification step using wavelet coefficients and Lipschitz exponents allows us to distinguish bursts from other transient events.

### 5.2 Localization Performance

After a burst transient is detected, the extremum of the detail coefficients is tracked across levels to estimate the arrival time of the transient. The arrival times from the three measurement points are provided to the burst localization algorithm. The approximate graph model for the localization algorithm consists of 8 nodes: 3 measurement points and 5 main pipe junctions, shown in Fig. 3b. In addition, the distances between adjoining nodes and wave speed estimates for the different pipe sections are known. The localization results are shown in Table 2. The expected arrival time differences for (M1,M2) and (M1,M3) are 0.32255 s and 0.53128 s, respectively. The average localization error, based on these experiments, is 37.5 m. Although this is not accurate enough to determine the exact location of the burst, it can help identify the section of the pipe that has to be isolated. A pipe section of this length can be inspected for leaks in a small amount of time using established leak-detection techniques such as acoustic correlators [14]. The location time will be significantly reduced using the proposed techniques when compared to current practice.

| Table 2 Burst localization results. |
|--------------------------------------|
| Burst event | Arrival time difference (in sec) | Localization error (in m) |
| $t_{M2} - t_{M1}$ | $t_{M3} - t_{M1}$ | $t_{M3} - t_{M2}$ |
|--------------|----------------|----------------|----------------|
| 1 | 0.22569 | 0.50659 | 0.28090 | 48.94 |
| 2 | 0.23283 | 0.58026 | 0.34743 | 46.36 |
| 3 | 0.24376 | 0.62510 | 0.38750 | 43.79 |
| 4 | 0.30847 | 0.50630 | 0.19783 | 10.30 |
| 5 | 0.25034 | 0.51397 | 0.26363 | 36.06 |
| 6 | 0.32234 | 0.58760 | 0.26411 | 2.72 |
| 7 | 0.19798 | 0.46865 | 0.27067 | 61.82 |
| 8 | 0.26800 | 0.67075 | 0.40275 | 28.33 |
| 9 | 0.20791 | 0.54931 | 0.34140 | 59.24 |
| Expected | 0.32255 | 0.53128 | 0.20873 | – |

Table 1 Burst event detection results.

| Measurement point | True detections | False detections | Missed events |
|-------------------|-----------------|-----------------|---------------|
| Multiscale wavelet analysis | M1 | 9 | 1 | 0 |
| | M2 | 9 | 0 | 0 |
| | M3 | 9 | 0 | 0 |
| CUSUM change detection test | M1 | 9 | 18 | 0 |
| | M2 | 9 | 8 | 0 |
| | M3 | 9 | 12 | 0 |
Table 3 Worst-case error induced in distance estimation by using the PPS GPS signal for on-node clock synchronization.

| Pipe diameter | Pipe material   | Estimated wave speed | Distance estimation error |
|---------------|-----------------|----------------------|--------------------------|
| 500 mm        | Steel           | 1030.3 m/s           | 1.03 m                   |
| 300 mm        | Ductile iron    | 1088.7 m/s           | 1.09 m                   |

6 Localization Error Analysis

In this section we discuss some of the sources of error in burst localization and attempt to quantify their impact on the localization result.

6.1 Time Synchronization

Time synchronization is very important for relating events observed in the data gathered across a sensor network. The time synchronization accuracy that is required in a sensing system depends on data usage. In this case, accurate time synchronization is vital to correlate pressure transients in order to localize a leak or burst event. Since the wave speed propagation carrying a pressure transient in a pipe is in the region of 1000 m/s, every millisecond of accuracy is important. We examine the Network Time Protocol (NTP) logs to quantify the stability of the PPS method and relate this to the potential localization error. NTP changes the local clock time to best match the reference time, so a stable clock will see small adjustments, whereas a highly variable reference clock will see large adjustments, potentially making the local clock unstable for fine grained measurements. We examine clock offset data taken under normal node operation over a six day period. It is observed that with the PPS input, the clock changes made by NTP are within ±1 ms. In comparison, the Internet reference timings arrive over a highly variable network connection (in terms of latency) to reach the node. The clock changes made by NTP reflect this, being around ±130 ms, or two orders of magnitude larger than when using PPS.

Since the main motivation for time synchronization in this case is for event detection and localization, it follows that errors in timing observed by NTP affect the accuracy bounds of localization. Using the wave speed estimates, we can estimate the relative impact of the clock offsets on distance estimation and therefore the localization results. Table 3 shows the error that could be induced using the PPS signal from a GPS module to synchronize a node’s local clock. We see that if the local clock is offset from the reference time by ±1 ms, this translates to a worst-case uncertainty of 1.09 m.

Figure 5 Wave speed estimates as a function of the distance of the measurement point from the burst location.
This is acceptable given the inter-node distances along pipelines are of the order of 500 m (thus 1.09 m error is just 0.2 % of the inter-node distance).

6.2 Wave Speed Estimation

The wave speed in a pipe depends on parameters such as the pipe dimensions (diameter and thickness), pipe material and properties of the fluid flowing through the pipe (water with entrained air). We performed a separate set of emulated burst experiments which were used for estimating wave speeds in the pipe sections. In these experiments, burst events were emulated at various locations within the test bed. In addition to the burst emulation equipment, a mobile sensor node (recording pressure data) was also attached to the fire hydrants at each of these locations. This sensor node allows us to record the time at which the burst transient originated from the source. We then use the time at which the transient is detected at the other measurement point(s) along the same pipe section to compute the wave speed estimate for that pipe section.

The results from these experiments are shown in Fig. 5, where we plot the wave speed estimates for both the 300 mm ductile iron and 500 mm steel pipes as a function of the distance of the measurement point from the burst location.

It is seen that most wave speed estimates are in the region of 1000 m/s for both pipe types. We use the mean value of these estimates as the wave speeds for the localization experiments (reported earlier in Section 5).

Next, we would like to determine how variation in the wave speed estimates around their true values would affect the localization error. For this purpose, let us assume that the mean wave speed values obtained above are the actual (or true) wave speeds. We introduce error into these mean values and use the resulting values as the estimated wave speeds. Error in the wave speeds, with the other parameters being constant, would translate to an error in the expected arrival time differences. The arrival time differences determine the score metric (Eq. 4) which is used as the objective function for the localization. Thus, we can assume that the error in arrival time differences is approximately linearly related to the localization error. This linear relationship between the localization error and the error in arrival time differences (rms error) is obtained empirically using an /l1-norm fit for the localization data presented in Table 2.

Figure 6 shows the localization error as a function of the estimated wave speeds in the 500 mm pipe.
steel and 300 mm ductile iron pipes. Using the estimated wave speeds, we compute the expected arrival time difference, which is then compared with the arrival time difference based on the actual wave speeds, difference between the two giving the error in arrival time difference. Finally, the arrival time difference error is translated to an error in localization using the empirically derived relationship above. It is seen that the localization error attains its minimum value when the estimated wave speeds equal the actual wave speeds in the two pipes. It can also be seen that ±10% error in wave speed estimation results in a worst case 20% error.

![Denoised pressure signal](image1)

(a) Burst transient recorded at M3 showing two arrivals via different paths.

![Denoised pressure signal](image2)

(b) Wavelet detail coefficients.

**Figure 7** Illustration of two interfering transients: Transient recorded at M3 and the corresponding detail coefficients.
degradation in the localization performance (localization error increases from around 41 m to 50 m).

6.3 Arrival Time Estimation

The burst arrival time estimation is challenging due to two effects: (i) interfering transients and (ii) attenuation of the pressure transient as it propagates along the pipes causing dispersion. During our experiments, the burst transient appeared to take two paths to reach M3 which interfere with each other. The two paths from B to M3 are shown on the network layout in Fig. 3a. This is also illustrated in Fig. 7 with the detail coefficients registering the two transient arrivals. The time difference between the two transient arrivals is around 0.4 s which matches well with the difference in the two path lengths of around 500 m. Thus, in cases where two arrivals were detected, the first arrival time was used for the burst localization. The arrival time estimation problem is also exacerbated by the fact that a burst-induced transient is attenuated by friction in the pipes, causing dispersion that reduces the slope or steepness of the transient as it propagates.

6.4 Sensor Locations and Inter-node Distance Measurement

The inter-node distances and locations of the measurement points were obtained via surveying techniques such as GPS. Typical standalone GPS survey units can result in positioning errors of around ±5 m.

6.5 Localization Sensitivity Analysis

In the preceding sub-sections we identified the sources of localization error and quantified the effect of each parameter (to an extent independently) on the localization performance. We next attempt to visualize the sensitivity of the localization result to errors in the arrival time and wave speed estimates.

We perform Monte Carlo simulations assuming worst case errors of ±100 ms in arrival time estimation and ±100 m/s in wave speed estimation. This arrival time estimation error is assumed to include the effects mentioned in Section 6.3 as well as the time synchronization error. The localization result from each simulation is mapped to the nearest junction or vertex in the pipe network model and at the end of all the simulation runs a probability map of the localization result is generated providing a confidence measure for the results. The result from 675 such simulation runs is shown in Fig. 8.

This provides an estimate of the uncertainty in the localization result given some knowledge of the errors in the estimation of the various parameters. It can be seen that the probable burst locations are within 100 m of the actual burst location and the most probable burst location is around 56 m from the actual burst location. The probabilistic map can be used to identify the general area in which the suspected leak resides, providing a starting point for more detailed inspection, using acoustic correlation or similar techniques [8, 14]. In this case, acceptable localization error is on the order of tens of meters (less than 100 m), with increased error...
having a direct impact on the time required to locate the leak as a greater length of pipe must be searched.

7 Future Work

The algorithms and results presented here are based on two sets of experiments where the bursts were emulated above ground using a solenoid-activated valve. The results indicate that the proposed techniques hold promise. The next program of tests will include more realistic emulation of underground pipe bursts and comparison of acoustic and pressure transient detection methods. The long-term goal is to establish limits on detection capabilities relating to the burst size and distance from the source of the burst. In addition, we are also working on extending the wavelet-based event detection scheme and graph-based localization algorithm to some of the slow transient events such as slow leaks, valve and other maintenance operations.

8 Conclusion

The wavelet-based burst event detection and graph-based localization technique presented in this paper shows promise for continuous monitoring of transient events in a water distribution network. The technique is based on real-time continuous monitoring of pressure and can minimize the detection and localization time of these events. The technique was verified using the WaterWiSe@SG test bed deployed on the water distribution network in Singapore. The technique was shown to be robust to impulsive noise and able to distinguish burst transients from other operational events. Only three measurement points are sufficient to uniquely determine the location of the burst. A systematic study of the sources of localization error was also presented.

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