Wavelet-based Burst Event Detection and Localization in Water Distribution Systems

Journal of Signal Processing Systems manuscript No.
(will be inserted by the editor)

Wavelet-Based Burst Event Detection and Localization in Water Distribution Systems

Seshan Srirangarajan · Michael Allen · Ami Preis · Mudasser Iqbal · Hock Beng Lim · Andrew J. Whittle

Received: date / Accepted: date

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, we also present a systematic analysis of the sources of localization error.

Keywords Multiscale wavelet analysis · transient detection · pipe burst · burst localization

1 Introduction

Urban utilities such as drinking water distribution systems (WDSs) are critical infrastructures that increasingly large numbers of residents rely on daily. As populations in cities grow, the demand on these critical infrastructures also grows and the need for real-time monitoring and maintenance becomes vital to ensure efficient, reliable operation and timely response to

S. Srirangarajan
Nimbus Center, Cork Institute of Technology, Ireland
Tel.: +353-21-4335166
E-mail: seshan.srirangarajan@cit.ie

M. Allen and A. Preis
Singapore-MIT Alliance for Research and Technology, Singapore

M. Iqbal and H. B. Lim
Intelligent Systems Center, Nanyang Technological University, Singapore

A. J. Whittle
Department of Civil and Environmental Engineering, Massachusetts Institute of Technology, USA

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. 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.

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 a 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 denoised 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 gives more detail on pipe bursts and existing event detection/localization techniques, with specific reference to water distribution systems; Section 3 presents our wavelet-based event detection scheme and Section 4 presents our graph-based localization algorithm. Section 5 presents evaluation of the detection and localization techniques, including performance and error source analysis. Finally, Sections 7 and 8 draw conclusions and identify areas for future work.

2 Background

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 [9]. 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). The pulse is reflected by pipe junctions and end-points in the physical network, and its speed is altered by the pipe material and diameter as it travels through the network. The transient is also attenuated by friction in the pipes, causing dispersion that reduces the slope or steepness of the transient wavefront. The pressure transient, when detected at a number of measurement points can provide information on the location of the burst (see Figure 4 for an indicative set of pressure traces).

The burst (and subsequent leak) also create distinct acoustic emissions, changing the background acoustic signature of the pipe [1]. 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) [6, 2]. 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 pressure transients are less readily attenuated and the pressure signature is relatively unaffected by background noise (e.g., traffic) than acoustic emissions, increasing the distance over which they can be reliably detected.

Event detection in general is an elaborately studied research area [4]; specifically in the context of a WDS, Misiunas et al. propose a method for detecting the pressure transient associated with a burst event using the cumulative sum (CUSUM) change detection test [10]. 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.

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 [15] or pulmonary microvascular pressure signals [7]. Wavelet analysis has also been proposed to detect transients in pressure signals for leak detection and location in water pipelines [13].

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.

Techniques for detecting and locating pipe bursts in WDS have also been studied in the literature, although most of these techniques consider single pipelines and have not been applied to network systems [12, 11]. 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 [11], in controlled laboratory environments [13, 10], or in transmission pipelines which are immune from pressure variations due to demand fluctuations [9]. 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 [9]. 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 wave transmission coefficients. 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

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. Conversely, pipe burst events result in a sudden change in the flow through the pipe, producing a pressure transient which must be detected over time scale from milliseconds to seconds. In this paper, we assume that pressure has been sampled at 250 Hz in order to adequately capture the transients at all time scales. Appropriate down-sampling is applied for longer time-scale transients.

Figure 1 shows an outline of the proposed wavelet analysis based event detection scheme. 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 250 Hz raw pressure signal. This de-noised pressure signal is used for detecting burst transients. In addition, the de-noised pressure signal is low-pass filtered (for anti-aliasing) and downsampled to $1/30$ Hz for detecting slow transients (such as slow leaks and valve operations).

The pressure signal is then 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. A 4-level decomposition was found to be a good fit for the pressure data being analyzed. 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. 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 [8]. 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

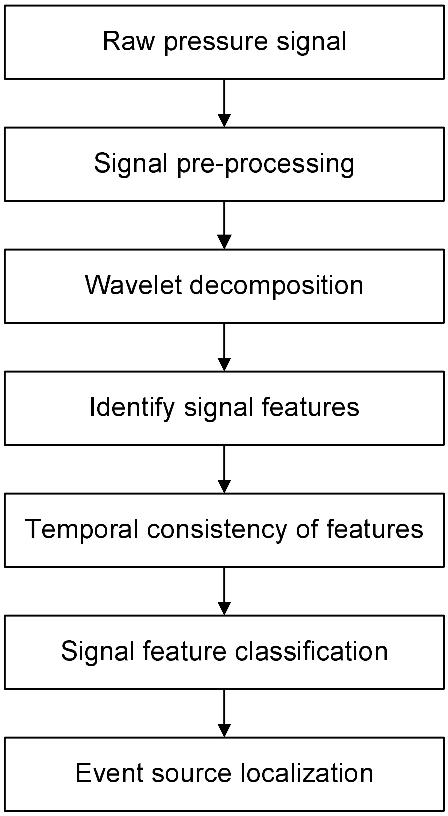


Fig. 1 Wavelet-based event detection scheme.

as a possible signal feature. Figure 2 illustrates the wavelet analysis for a typical pressure transient signature due to an emulated burst event.

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 $(N-1)$ detail, would be represented by only around $m/2$ samples at level N. Thus, the temporal spread of a feature (Δt) across N levels of scale must satisfy the following condition:

$$\Delta t \leq 2^N \cdot T_s \tag{1}$$

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

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 [8]. The Lipschitz exponent (α) of a signal feature, around time t_{sf}, can be approximated as [5]:

$$\alpha = \log_2 M_{j+1} - \log_2 M_j \tag{2}$$

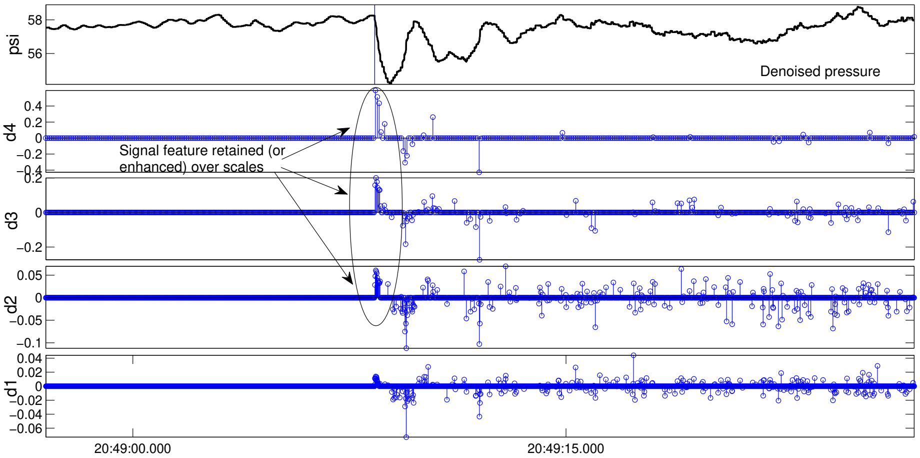


Fig. 2 Multiscale wavelet analysis: Identifying signal features.

where $M_j = \left|W_j\left[p_d(t_{sf})\right]\right|$ is the local wavelet transform modulus maxima of the de-noised pressure signal p_d around time t_{sf} at scale 2^j. 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. 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.

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 Figure 2, that extremum of the detail 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 Figure 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 (τ_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 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. It is likely that this 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 [3]. Let τ_{jk} represent the travel time from node j to k. If the burst occurs at node i, where $i = 1,\ldots,N$ (N = number of nodes in the network) then:

$$(t_j - t_k) - (\tau_{ij} - \tau_{ik}) = 0. \tag{3}$$

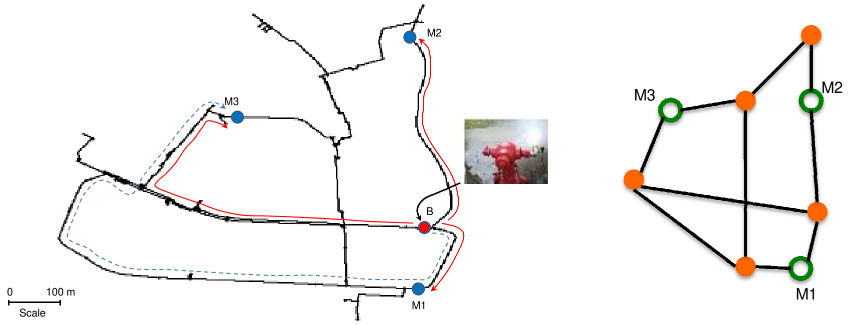
However, due to timing, measurement and other errors, the left-hand side of (3) will never be zero. Thus, to identify the burst location, a search algorithm is proposed. The search is divided into two steps:

– ***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 (3), for each node i in the network we compute a score (or error metric) s_i given by:

$$s_i = \sum_{\substack{j,k \in S_B \\ j \neq k}} |(t_j - t_k) - (\tau_{ij} - \tau_{ik})| \tag{4}$$

  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 (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.



(a) Pipe network layout for a portion of the WDS.

(b) Corresponding graph model for a portion of the WDS.

Fig. 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.

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 water distribution system in Singapore [14, 1]. The test bed consists of wireless sensors measuring hydraulic and water quality parameters in real-time. Pressure measurements are recorded at a sampling frequency of 250 Hz, and the wireless sensors are synchronized to a common time frame using the Pulse Per Second (PPS) feature of their on-board GPS modules.

The bursts were emulated using a 2-inch diameter solenoid valve with a nominal opening time of 0.1 sec. 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 consist 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 (wave speed estimation is discussed further in Section 6.2). The pipe network layout for the test bed and the equivalent graph model are shown in Figure 3, covering an area of around 1 km^2. 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 hours. 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 hour experimentation period was analyzed using the multiscale wavelet algorithm, implemented in Matlab. A typical pressure transient signature at the three measurement points from one of the emulated burst events is shown in Figure 4. As a point of comparison to existing approaches, we also implemented the CUSUM change detection test [10]. It was noted by the authors that the CUSUM technique is susceptible to false positives, caused by non-burst pressure transients such as pump shutdowns, valve operations or

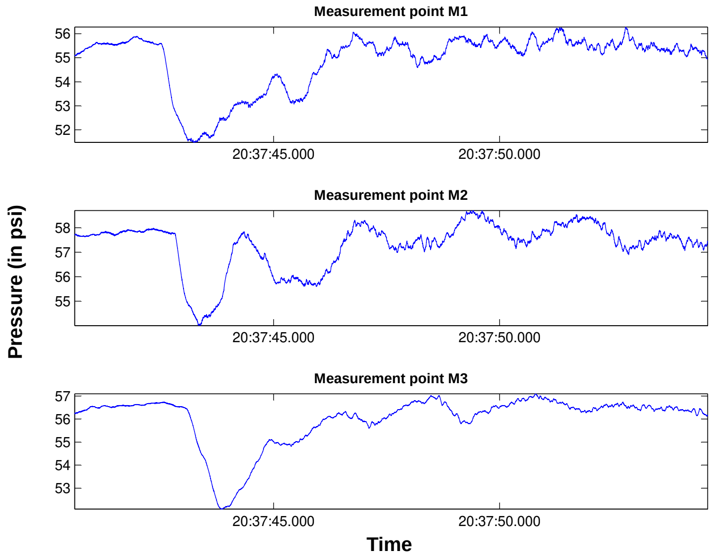


Fig. 4 Pressure transient signature at the three measurement points from one of the emulated burst events.

	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 1 Burst event detection results.

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 threshold h and drift ν parameters, of the CUSUM test were tuned such that all the emulated bursts were detected. The detection results, for the 2 hour 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. The feature classification step using the wavelet coefficients and the Lipschitz exponents allows us to distinguish bursts from other transient events.

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	0.23760	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	0.32349	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 time differences	0.32255	0.53128	0.20873	

Table 2 Burst localization results.

5.2 Localization Performance

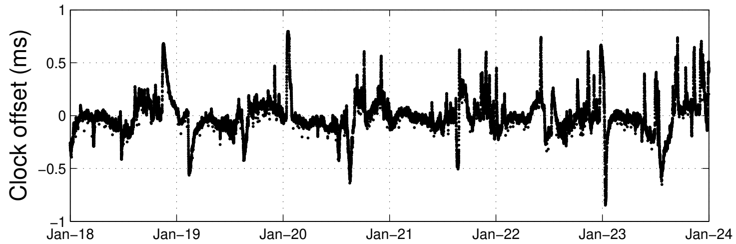
After a burst transient is detected, the extremum of the detail coefficients is tracked across levels to estimate the arrival time of the transient. The arrival times from the three measurement points are provided to the burst localization algorithm. The approximate graph model for the localization algorithm consists of 8 nodes: 3 measurement points and 5 main pipe junctions, shown in Figure 3(b). 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 sec and 0.53128 sec, 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. The location time will be significantly reduced using the proposed techniques when compared to current practice.

6 Localization Error Analysis

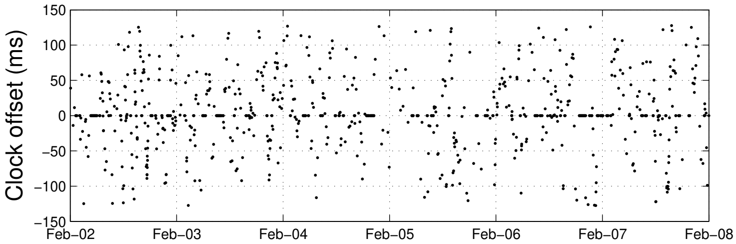
In this section we discuss some of the sources of error in burst localization and attempt to quantify their impact on the localization result.

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



(a) Using PPS/GPS data.



(b) Using only Internet NTP servers.

Fig. 5 Comparative local clock offset values when PPS/GPS is used and when only Internet NTP servers are used, both taken from the same node, over a six-day period. Note that the offset values, and hence clock error, are two orders of magnitude higher when only Internet accessible NTP servers are used.

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. Figure 5 shows the stability of local clock changes when PPS GPS data is provided to NTP (top plot), and when the only reference time source is an Internet-based NTP server (bottom plot). The x-axis is time, and the y-axis represents the amount by which NTP has changed its local clock to best match the reference clock. Both sets of data were taken under normal node operation over a six day period. We see that under normal operation (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. 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).

Pipe diameter	Pipe material	Estimated wave speed	Distance estimation error	
			PPS/NTP ($\pm$ 1 ms)	NTP server ($\pm$ 130 ms)
500 mm	Steel	1030.3 m/s	1.03 m	133.94 m
300 mm	Ductile iron	1088.7 m/s	1.09 m	141.53 m

Table 3 Worst-case error induced in distance estimation by using the PPS GPS signal for on-node clock synchronization.

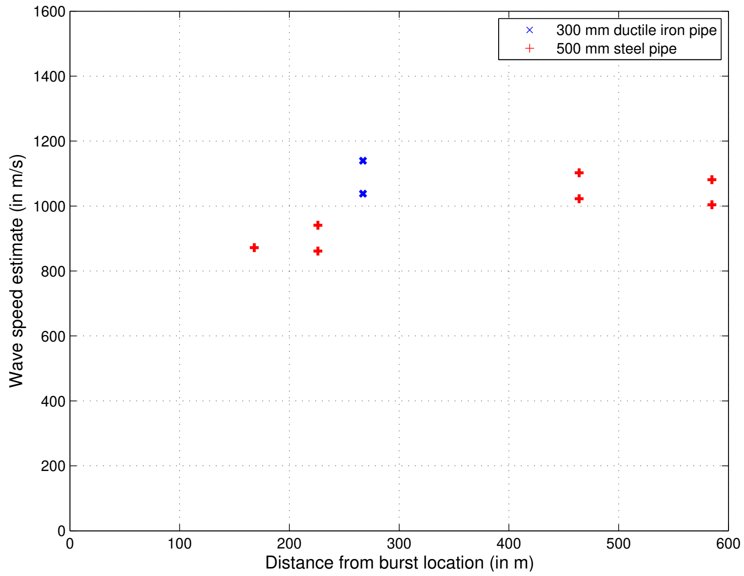


Fig. 6 Wave speed estimates as a function of the distance of the measurement point from the burst location.

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 Figure 6, 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).

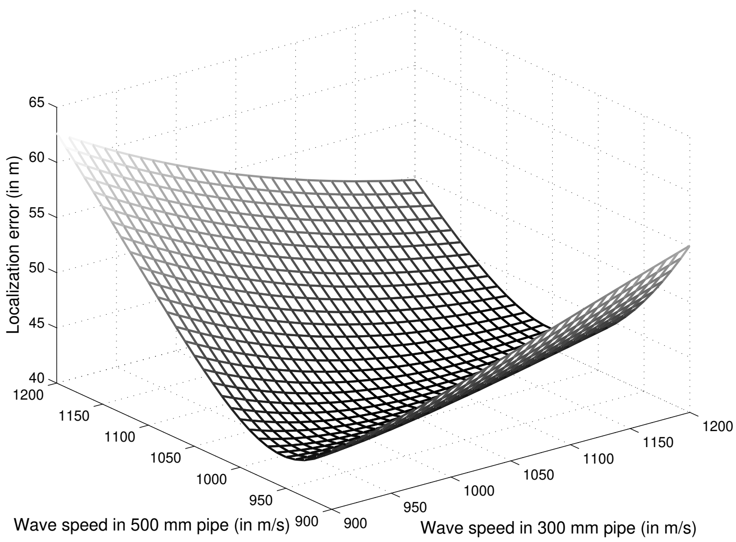
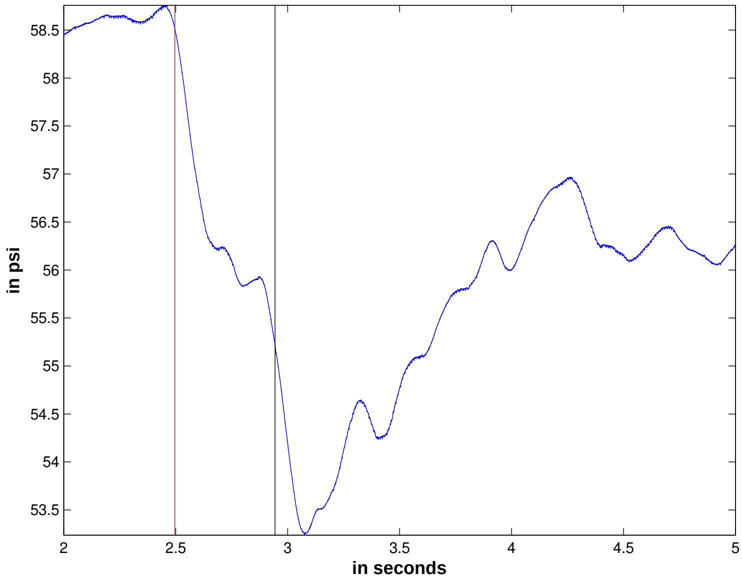


Fig. 7 Localization error as a function of the wave speeds.

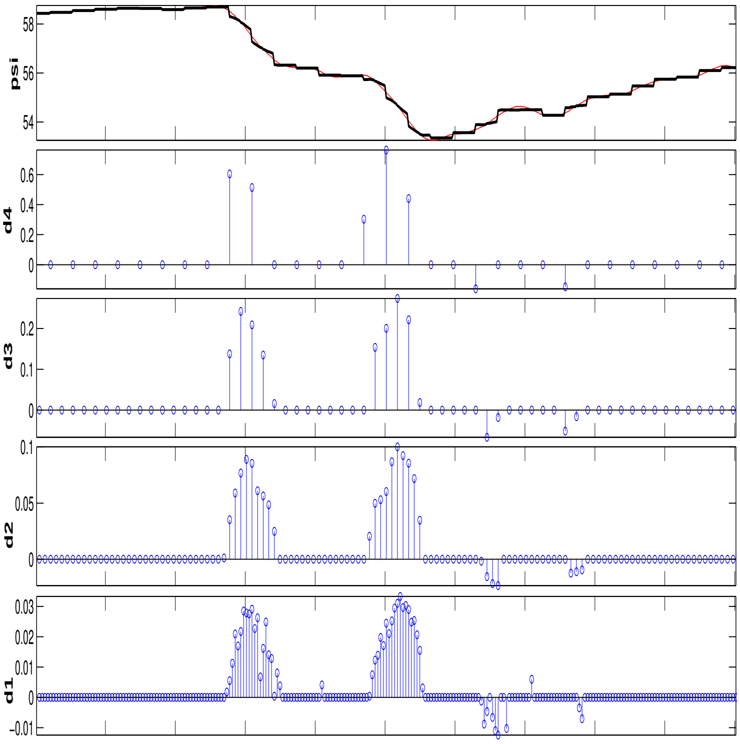
Next, assuming that the wave speed estimates obtained using the above method are accurate, we attempt to relate error in wave speed estimation to the localization error. Any error in wave speeds, other parameters being constant, would translate to an error in the expected arrival time differences which can be assumed to be linearly related to the localization error. This linear relationship between the localization error and the error in arrival time differences (rms error) is empirically obtained using an $l1$-norm fit for the localization results presented in Table 2. Thus, the effect of wave speed estimation error on localization is shown in Figure 7. It can be seen that even a 10% error in wave speed estimation can severely degrade the localization performance.

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 Figure 3(a). This is also illustrated in Figure 8 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.



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



(b) Wavelet detail coefficients.

Fig. 8 Illustration of two interfering transients: Transient recorded at M3 and the corresponding detail coefficients.

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 Sensitivity Analysis

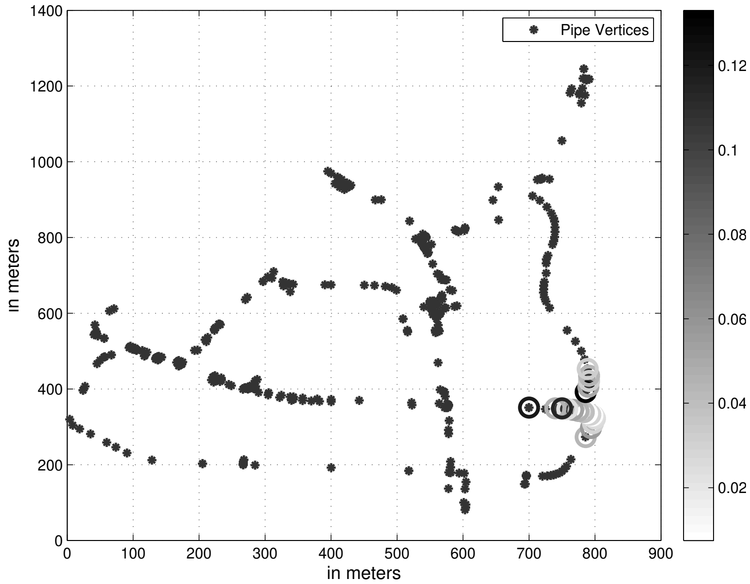
In the preceding sub-sections we identified the sources of localization error and quantified the effect of each parameter (to an extent independently) on the localization performance. We next attempt to visualize the sensitivity of the localization result to variation in the wave speed and arrival time 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. 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 Figure 9. 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. Thus, the localization results are within acceptable error limits even with large estimation errors.

7 Future Work

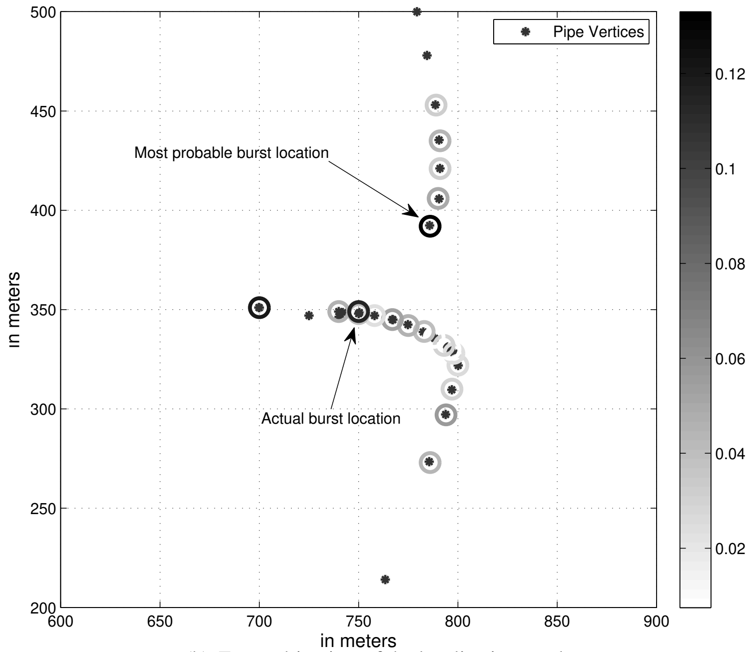
The algorithms and results presented here are based on two sets of experiments where the bursts were emulated above ground using a solenoid-activated valve. The results indicate that the proposed techniques hold promise. The next program of tests will include more realistic emulation of underground pipe 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.



(a) Localization result as a probability map.



(b) Zoomed-in view of the localization result.

Fig. 9 Localization result as a probability map providing a confidence measure. Probable burst locations are indicated by circles around the system nodes and the color of these circles gives the confidence measure (or probability) of that being the burst location.

Acknowledgements This work is a collaboration between the Center for Environmental Sensing and Modeling (CENSAM) - Singapore-MIT Alliance for Research and Technology (SMART), Intelligent Systems Center (IntelliSys) at Nanyang Technological University (NTU) and Singapore Public Utilities Board (PUB). This research is supported by the Singapore National Research Foundation (NRF) through the Singapore-MIT Alliance for Research and Technology (SMART) Center for Environmental Sensing and Modeling (CENSAM). We would like to acknowledge our colleagues Cheng Fu, Lewis Girod and Kai-Juan Wong for their contributions.

References

1. Allen, M., Preis, A., Iqbal, M., Srirangarajan, S., Lim, H.B., Girod, L., Whittle, A.J.: Real-time in-network distribution system monitoring to improve operational efficiency. Journal American Water Works Association (AWWA) **103**(7), 63–75 (2011)
2. Brennan, M., Joseph, P., Muggleton, J., Gao, Y.: The use of acoustic methods to detect water leaks in buried water pipes. Water and Sewerage Journal **1**, 11–14 (2006)
3. Dijkstra, E.W.: A note on two problems in connexion with graphs. Numerische Mathematik **1**, 269–271 (1959). Http://www-m3.ma.tum.de/twiki/pub/MN0506/WebHome/dijkstra.pdf
4. Guralnik, V., Srivastava, J.: Event detection from time series data. In: Proc. 5th ACM SIGKDD Int. Conf. Knowledge Discovery and Data Mining, pp. 33–42 (1999)
5. Hu, X.G., Ji, Y.C., Yu, W.B.: The application of wavelet singularity detection in fault diagnosis of high voltage breakers. In: 27th Annual Conf. of the IEEE Industrial Electronics Society (IECON ’01), vol. 1, pp. 490–494 (2001)
6. Hunaidi, O., Wang, A., Bracken, M., Gambino, T., Fricke, C.: Acoustic methods for locating leaks in municipal water pipe networks. In: Int. Conf. on Water Demand Management, pp. 1–14 (2004)
7. Karrakchou, M., Kunt, M.: Multiscale analysis for singularity detection in pulmonary microvascular pressure transients. Annals of Biomedical Engineering **23**, 562–573 (1995)
8. Mallat, S., Hwang, W.L.: Singularity detection and processing with wavelets. IEEE Transactions on Information Theory **38**(2), 617–643 (1992)
9. Misiunas, D.: Failure monitoring and asset condition assessment in water supply systems. Phd thesis, Lund University (2005)
10. Misiunas, D., Lambert, M., Simpson, A., Olsson, G.: Burst detection and location in water distribution networks. Water Science and Technology: Water Supply **5**(3) (2005)
11. Misiunas, D., Vitkovsky, J.P., Olsson, G., Simpson, A.R., Lambert, M.F.: Pipeline burst detection and location using a continuous monitoring technique. In: Advances in Water Supply Management: Int. Conf. on Computing and Control for the Water Industry (CCWI), pp. 89–96 (2003)
12. Silva, R.A., Buiatti, C.M., Cruz, S.L., Pereira, J.A.F.: Pressure wave behaviour and leak detection in pipelines. Computers and Chemical Engineering **20**(Supplement 1), S491–S496 (1996)
13. Stoianov, I., Karney, B., Covas, D., Maksimovic, C., Graham, N.: Wavelet processing of transient signals for pipeline leak location and quantification. In: Int. Conf. on Computing and Control for the Water Industry (CCWI), pp. 65–76 (2001)
14. Whittle, A.J., Girod, L., Preis, A., Allen, M., Lim, H.B., Iqbal, M., Srirangarajan, S., Fu, C., Wong, K.J., Goldsmith, D.: WaterWiSe@SG: A testbed for continuous monitoring of the water distribution system in Singapore. In: Proc. 12th Water Distribution Systems Analysis Conference (WDSA) (2010)
15. Zhang, H., Thurber, C.H., Rowe, C.: Automatic P-wave arrival detection and picking with multiscale wavelet analysis for single-component recordings. Bulletin of the Seismological Society of America **93**(5), 1904–1912 (2003)