WATER MAIN BURST EVENT DETECTION AND LOCALIZATION

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Abstract

In this paper we present a technique for detecting and locating burst events in pipelines. The proposed method uses wavelet analysis of the high-rate pressure data to detect pipe burst events. Multiscale wavelet analysis of the pressure signal will be shown to be robust to impulsive noise encountered in the physical phenomena under observation. The wavelet coefficients also allow us to obtain additional information about the nature of the signal feature detected, which can used for further feature classification. A local search method is also proposed to accurately determine the arrival time of the pressure front associated with the burst event. The detection performance of these algorithms is verified through leak-off experiments performed on the WaterWiSe@SG test bed deployed on the water distribution system in Singapore. We also propose a graph-based search algorithm which uses the arrival times of the pressure front at different locations within the water distribution system to determine the actual location of the pipe burst event.

Keywords
Pipe burst, multiscale wavelet analysis, transient detection, localization.

1 INTRODUCTION

Large-scale urban utility infrastructures are critical systems that affect a large number of people and thus call for proper monitoring and maintenance. A city-wide water distribution system (WDS) is one such infrastructure. Sudden pipe bursts can occur in high-pressure water transmission mains and distribution pipelines. These events can be very expensive due to the outage time while the burst pipe is repaired, the cost of repair, and damage to surrounding property and infrastructure. As a result, it is advantageous to minimize the detection and location time after the burst event occurs. Currently, the high cost of continuous monitoring of the WDS limits the data collection to a small number of locations. The advances in sensor network technology has enabled continuous monitoring of physical environments for long periods (days, months or even years) and detection of events in environments that are difficult to access.

There have been some proof-of-concept efforts in the past for developing a WDS monitoring system (Stoianov et al. 2006; Stoianov et al. 2007). Techniques for detecting and locating 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 (Silva et al. 1996; Misiunas et al. 2003). For example, Misiunas et al. propose a method for detecting the pressure transient associated with a burst event using the cumulative sum (CUSUM) change detection test (Misiunas et al. 2005). 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 (Zhang et al. 2003), pulmonary microvascular pressure signals (Karrakchou and Kunt 1995). Wavelet analysis has been applied to detect transients in pressure signals for leak detection and location in water pipelines (Stoianov et al. 2001; Stoianov et al. 2002).

In the case of an ideal step edge, the position of the transition corresponds to position of 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 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. In addition, in a real water distribution network there are many operational events as well, such as pumping operations, valve opening/closure, which can interfere with the pressure transient associated with a burst event. This explains the need for an algorithm that extracts relations between features at different levels of scale and uses this to perform event detection.

Many 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 (Misiunas et al. 2003), in controlled laboratory environments (Stoianov et al. 2001; Misiunas et al. 2005), or in transmission pipelines which are immune from pressure variations due to demand fluctuations (Misiunas 2005). To our knowledge the work in this paper is the first instance of burst detection and localization algorithms being validated on a real urban-area WDS. Misiunas proposed a search-based burst localization technique (Misiunas 2005). 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.

In this paper we present a technique for detecting and localizing pipe burst events. The technique uses wavelet-based multiscale analysis of the pressure signal to detect burst 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 feature classification step then allows us to distinguish the (emulated) burst transients from other transient events. Since we are also interested in accurately determining the physical location of the burst event in the WDS, the multiscale analysis is combined with a focusing algorithm. The focusing algorithm determines the arrival time of the pressure transient at the measurement points starting from a rough estimate. Finally, we present a graph-based search algorithm which uses the arrival times of the transient at two or more measurement points to localize the burst event. This search algorithm is split into a coarse global search and a fine local search.

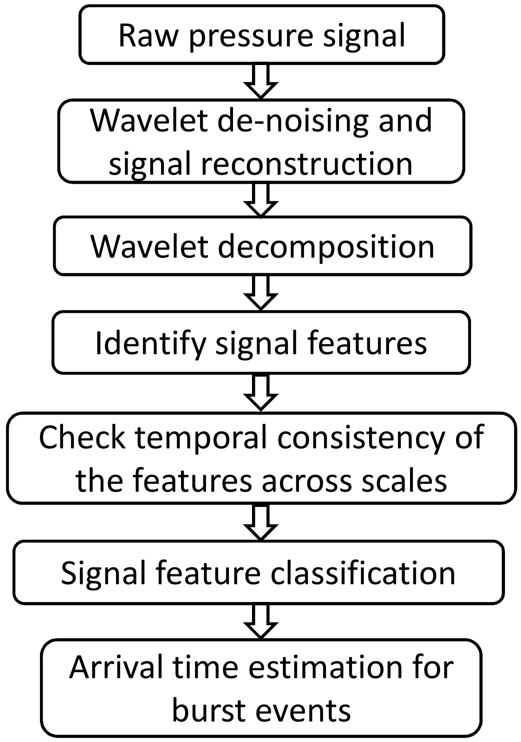


Figure 1. Wavelet-based event detection scheme.

2 BURST EVENT DETECTION USING MULTISCALE WAVELET ANALYSIS

Pipe burst events result in a sudden change in the flow through the pipe producing a pressure transient which propagates along the pipeline. This sudden decrease in pressure is followed by a partial recovery to its original value. This pressure pulse travels in both directions away from the burst origin at the wave speed of the pipe. The pulse is reflected by nodes and endpoints in the WDS, 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. (A typical pressure transient signature from an emulated burst event is shown in Figure 4.)

An outline of the proposed multiscale wavelet analysis algorithm for burst event detection is presented in Figure 1. As was mentioned above, the data acquired by the pressure sensors can contain impulsive noise as well as signatures due to operational events. The first step in the wavelet analysis is to apply wavelet de-noising to the raw pressure signal. The 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. A 7-level decomposition was found to be a good fit for the 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 denoised signal. The denoised signal is decomposed into 7 levels for further analysis.

In the next step, we identify signal features by considering the detail coefficients at levels 6 and 7 ($d6$ and $d7$), since the extremes of the details up to level 5 were found to be the result of both noise and signal features.

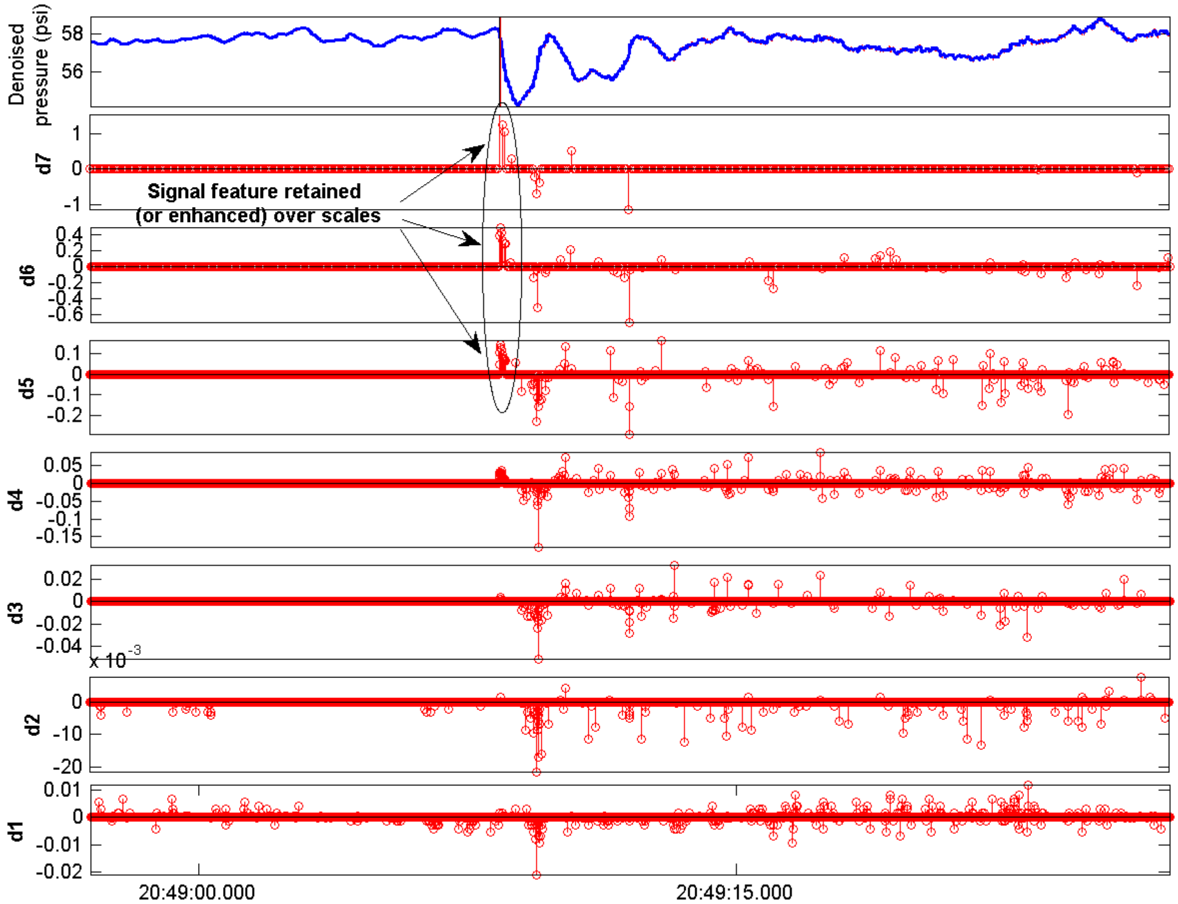


Figure 2. Multiscale wavelet analysis: Identifying signal features.

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 (Mallat and Hwang 1992). 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. This is illustrated in Figure 2. We next check the temporal consistency of each of the identified groups across scale. 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 presented 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 rule:

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

where T_s is the sampling period. These allow us to distinguish useful signal transitions from noise.

The wavelet coefficients provide additional information about the identified signal features which is used in the feature classification step. 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 nodes and endpoints, eventually returning to the baseline pressure in the pipe. On the other hand, some of the operational events such as value opening/closing are associated with an oscillatory pressure signature (i.e., a pressure rise either preceding or following a pressure drop). The magnitude and temporal spacing of the negative detail coefficients (if any) aids in the feature classification and allows us to identify burst transients.

Once a burst event is detected, we would like to localize the burst event. For this purpose, we need to 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 7 determines the approximate position of the transient. We then start from this level and move to lower levels to improve the localization 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.

3 GRAPH-BASED SEARCH ALGORITHM FOR BURST LOCALIZATION

We propose to determine the burst location using the difference in the burst arrival times at the measurement points in the WDS. In order to localize a burst event, the burst transient has to be detected at two or more measurement points. Before we present the localization algorithm, consider the following definitions in order to model the pipe network as a graph:

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

We assume that the measurement points are time synchronized and gather time tagged data. The burst event occurs at time t_B which is not known *a priori*. If the burst transient is detected at node 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 $t_i - t_B$ 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 (Dijkstra 1959). Let τ_{jk} represent the travel time from node j to k. If the burst occurs at node i, where $i = 1,\ldots,N$ (number of nodes in the network) then:

$$(t_j - t_k) - (\tau_{ij} - \tau_{ik}) = 0. \tag{2}$$

However, due to timing, measurement and other errors, the left-hand side of (2) will never be zero. Thus, to identify the burst location, a search algorithm is proposed. The search is divided into two steps:

3.1 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. For each node i in the network we compute a score (or error metric) s_i, based on (2):

$$s_i = \sum_{\substack{j,k \in S_B \\ j \neq k}} \left[(t_j - t_k) - (\tau_{ij} - \tau_{ik})\right]^2 \tag{3}$$

where S_B is the set of sensors that detected the burst transient. The smaller s_i is, the higher the 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.

3.2 Step 2: Search for the burst location along pipe sections connected to the nearest node

In this step, a new set of nodes is placed along the pipe sections connected to the node n 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 for the new set of nodes are recalculated and used to compute the scores (3). 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.

4 EXPERIMENTATION AND RESULTS

The performance of the proposed burst detection and localization algorithms is verified through leak-off experiments performed on the WaterWiSe@SG (Whittle et al. 2010) test bed deployed on the water distribution system in Singapore. The test bed consists of sensor nodes measuring hydraulic (pressure, flow) and water quality parameters. Pressure measurements were collected at a sampling frequency of 2000 Hz.

The bursts were emulated using a 2-inch diameter solenoid valve with a nominal opening time of 100 ms. A globe valve was used to control the discharge rate. The 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 1050 m/s and 1230 m/s, respectively. The pipe network layout is 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 sensor nodes) 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, 7L/s for event 5 and 5 L/s for events 6-9.

4.1 Burst Detection Performance

The pressure data from the above 2 hour 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. We also implemented the CUSUM change detection test (Misiunas et al. 2005). It was noted there that the CUSUM technique is susceptible to pressure transients initiated by a pump shutdown, a valve operation or a sudden increase in demand which can initiate pressure transients similar to the ones induced by the burst. The CUSUM test attempts to detect burst transients based on a rate of change criterion and does not attempt to classify the transient signatures. The parameters, threshold h and drift ν, of the CUSUM test were tuned such that all the emulated bursts were detected.

The detection results for the 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.

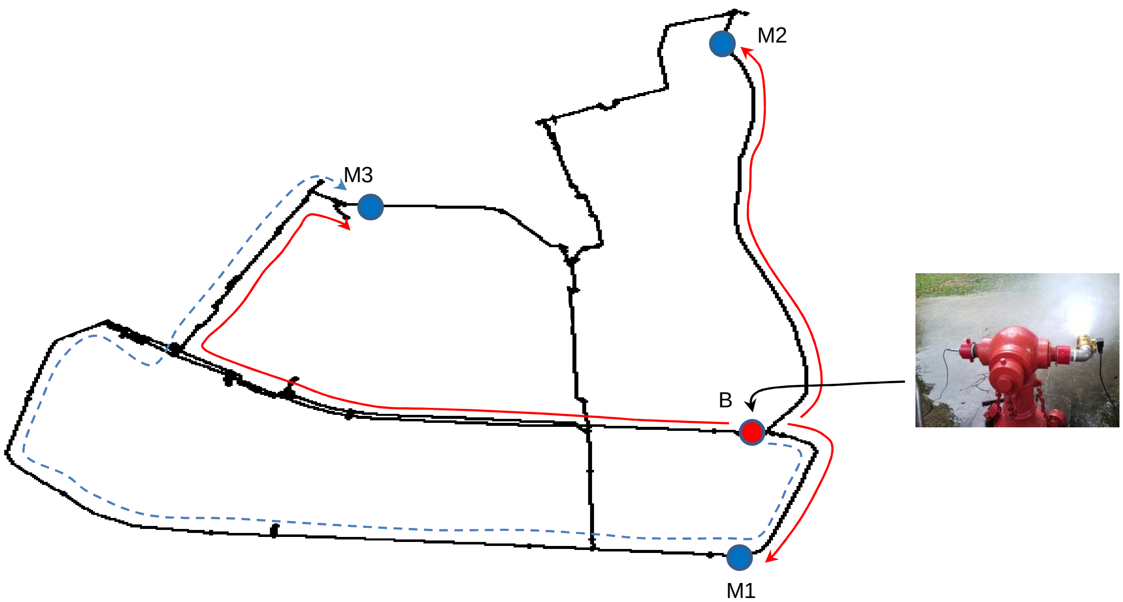


Figure 3. Network layout for a portion of the WDS. M1, M2 and M3 are the three measurement points (sensor nodes) and B is actual location of the burst events. The expected travel paths from B to the measurement points are shown in solid lines. The dashed path indicates a possible second path from B to M3.

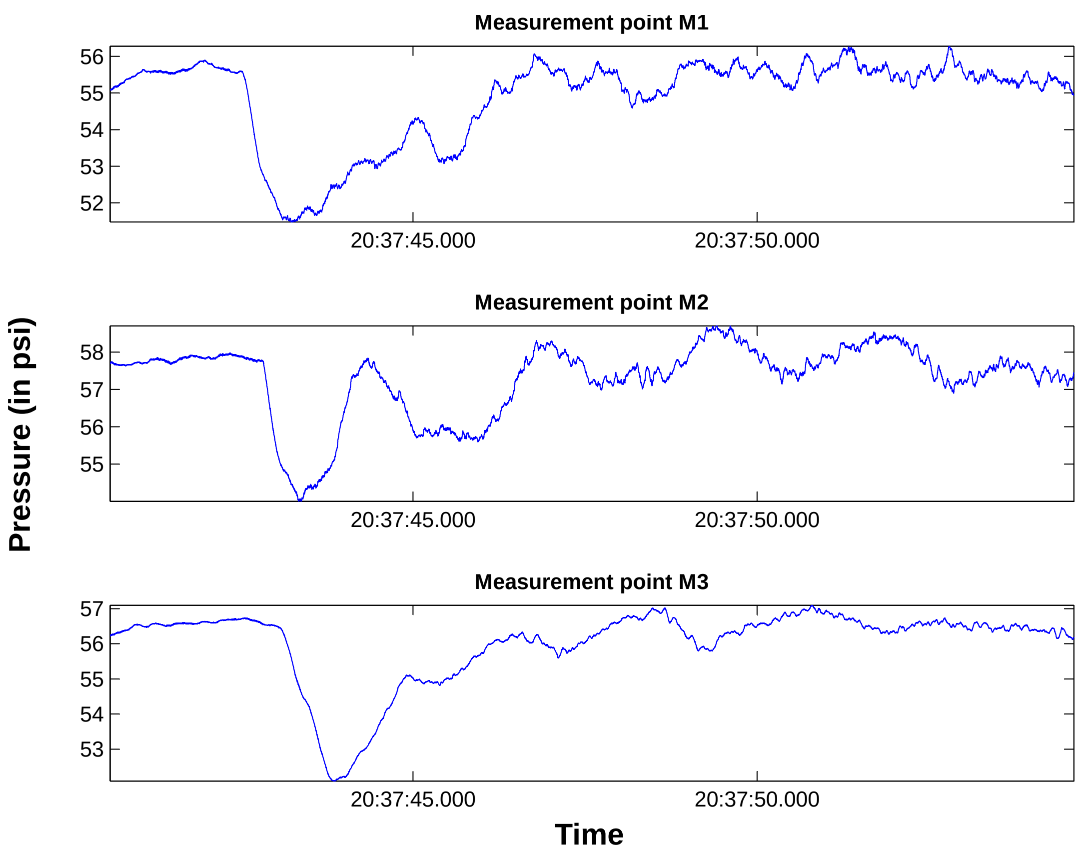


Figure 4. Pressure transient signature at the three measurement points from one of the emulated burst events.

	Measurement point	True detections	False detections	Missed events
Multiscale wavelet analysis	M1	8	1	1
	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.

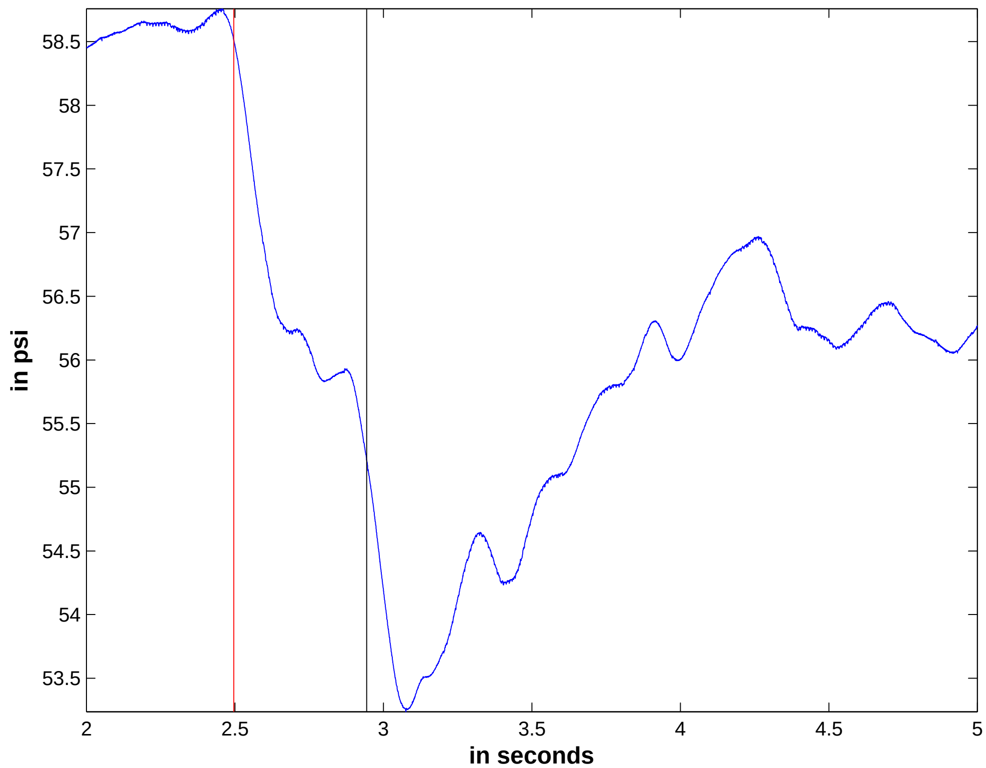
The wavelet-based algorithm was able to detect all events at M1, M2 and M3, except for one event at M1 and one false detection at M1. Burst event 8 (5 L/s) could not be detected at M1 as the burst signature was weak and could not be identified from the extremes of level 7 details. The feature classification step allows us to distinguish bursts from operational events.

4.2 Burst Localization Performance

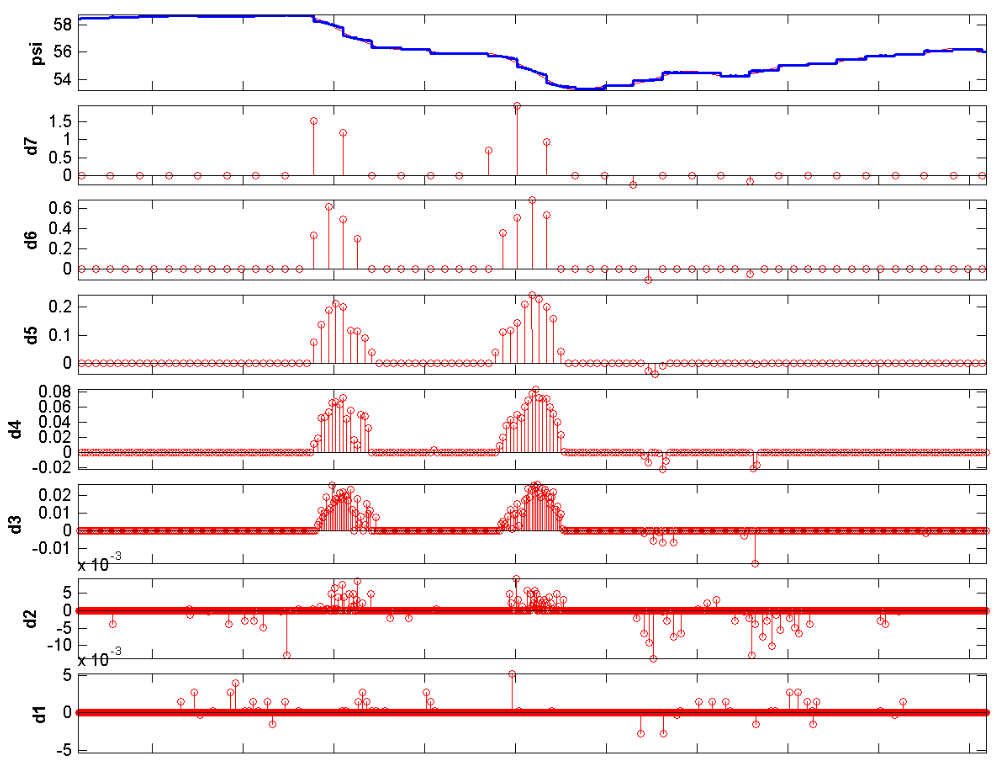
After a burst transient is detected, the extremum of the detail coefficients is tracked across levels to estimate the arrival time of the transient. The arrival times from the three measurement points are provided to the burst localization algorithm. The network model for the localization algorithm consists of 8 nodes (3 measurement points and 5 main pipe junctions), distances between adjoining nodes and wave speed estimates. The localization results are shown in Table 2. The expected arrival time differences for (M1,M2) and (M1,M3) are 0.34021 sec and 0.52193 sec, respectively. Burst event 8 could not be localized completely as only two of the measurement points detected this event. The average localization error is 46m. 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 in a small amount of time using sounding or other techniques to determine the precise burst location. The location time will be significantly reduced using the proposed techniques when compared to current practice.

4.3 Sources of Error

The inter-node distances and locations of the measurement points were obtained via surveying techniques such as GPS. These can have errors of around ±10 m. The wave speed estimation could be another source of error. The burst arrival time estimation could be affected by other interfering transients. It was observed that the burst transient seems 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. This is also illustrated in Figure 5 with the detail coefficients registering the two transient arrivals. In cases where two arrivals were detected, the first arrival time was used for the burst localization. The arrival time estimation problem is 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. In addition, the measurement points are time synchronized using the GPS pulse per second (PPS) signal resulting in typical timing errors of ±1.5 ms which translates to a distance error of around ±2 m.



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



(b) Wavelet detail coefficients.

Figure 5. Illustration of two interfering transients: Transient recorded at M3 and the corresponding detail coefficients.

Burst event	Arrival time difference (in sec)		Localization error
	$t_{M2} - t_{M1}$	$t_{M3} - t_{M1}$	(in m)
1	0.25768	0.50662	44.63
2	0.23283	0.58026	55.13
3	0.23764	0.62610	55.13
4	0.30851	0.50631	15.75
5	0.25034	0.51393	47.25
6	0.29147	0.55562	26.25
7	0.19798	0.50062	73.50
8	—	0.37071	—
9	0.23990	0.58127	52.50
Expected time differences	0.34021	0.52193	

Table 2. Burst localization results.

5 FUTURE WORK

We are exploring the use of the multiscale analysis technique in a more general event detection and classification framework where the goal would be to detect operational events such as valve or pumping operations and demand variations in addition to burst and leak events. This would allow us to update the hydraulic model of the WDS to better predict demands. The multiscale technique is also being studied in the context of detecting slow leaks. We are also trying to gain a better understanding into sources of the location error and how these can be mitigated.

6 CONCLUSION

The burst detection and localization technique presented in this paper shows promise for continuous monitoring of burst events in a real 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. Burst events of three different discharge rates were created, which were successfully detected and localized.

7 ACKNOWLEDGEMENTS

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