

Structural Health Monitoring With Whirlpool

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ABSTRACT

We propose a novel data delivery strategy, called Whirlpool, for efficient SHM using Wireless Sensor Networks. Whirlpool implements a rotating interrogation of a monitoring structure and provides collision-aware scheduling of the monitoring queries. The Whirlpool strategy can be tuned for the required Quality of Data (QoD). We apply Whirlpool to examine the unique properties of output signals of the structure under critical integrity conditions and to perform instability detection using redundancy-based estimation of Kolmogorov-Sinai entropy.

1. INTRODUCTION

SHM requires efficient collecting and analyzing of data obtained in response to ambient or forced excitation of the monitored system. Wireless sensor networks, which are easier to deploy than a wired sensor networks are a natural choice for implementing SHM [1]. However, SHM systems have special requirements with respect to efficient mechanisms for querying sensor data and delivering the query result in a timely manner. The data combined from all relevant sensors may be quite large and will require very high data transmission rates to satisfy time constraints. Meanwhile, limitations on sensor node resources like battery power imply that excessive transmissions in response to monitoring queries can lead to premature network death.

An examination of the reasons that affect both energy consumption and response time in sensor monitoring queries reveals that (a) data transmission *collisions* represent a major source of energy and time waste in wireless communications; (b) unnecessary amounts of *active time* for the sensors, due to lack of synchronization among data transmissions, is another major source of wasted energy and time in wireless sensor networks. In order to address each of above issues we develop *cross-layer query processing strategies* that fuse techniques from different areas of databases and networking [2].

In this paper we propose a novel *whirlpool* data delivery technique, which tunes the sensor query processing for specific performance and quality of data requirements of SHM systems. Whirlpool query processing is based on splitting the sensor network into *sectors* and performing a *rotating interrogation* over the sectors such that the complete network is monitored. Whirlpool introduces a natural *inter-sector concurrency* when two or more sectors can be interrogated simultaneously. The query optimizer also schedules concurrent data delivery within each whirlpool sector (*intra-sector concurrency*). We demonstrate the high utility of whirlpool in non-intrusive *SHM* that observes the natural dynamics of structure for changes that indicate damage or instability [3, 4, 5]. In particular,

using whirlpool, an SHM system can efficiently utilize the unique properties of chaotic output signals of the structure under critical integrity conditions.

2. SYSTEM MODEL

Consider a wireless sensor network deployed in order to monitor structural integrity. An example query over this network could request vibration data over a certain period of time. Answering this query would result in a tree-like data delivery pattern (Figure 1). This implies that the transmissions between sensors are *ad hoc* dependent on the query and require the use of a medium access control (MAC) layer to handle transmissions on the same medium and a routing algorithm that enables the nodes to select the right neighbor to transmit data.

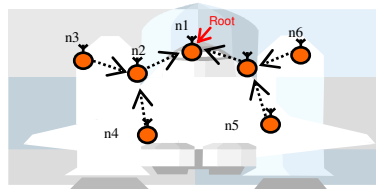


Figure 1: An example of a query tree

Popular wireless MAC layer technologies are the IEEE 802.11 standard for wireless local area networks [6] and the IEEE 802.15 standards for wireless personal area networks [7]. For low power and low data rate sensor networks, the 802.15.4 standard appears to be suitable. One issue, which is common for all MAC layer protocols, is proper handling of packet collisions. If we assume that all sensor nodes use the same frequency band for transmission, two transmissions that overlap will get corrupted (collide) if the sensor nodes involved in transmission or reception are in the same *collision domain* defined as the union of the transmission ranges of the communicating nodes. This is independent of the MAC protocol selected.

Recent study [1] has shown that common MAC protocols can achieve 100% data delivery reliability with a packet rate up to 1 packet/sec per node. This happens mainly because of a large number of packet losses that occur due to collisions. Meanwhile, the number of collisions can increase significantly if the load on the network increases. For example, it is reported in [8] that the successful packet delivery ratio in 802.15.4 can drop from 95% to 55% as the load increases from 1 packet/s to 10 packets/s. Consider an SHM system as described in [1]. Sensors in such systems can generate up to 20 kilo-samples/s on four channels for a total of 80 kilo-samples/s. Each sample is 16 bits long resulting in data being generated by each sensor at a rate of 1280 kbps (160 bytes/s). The maximum physical layer packet size in 802.15.4 is 127 bytes of which 16-32 bytes are part of the MAC/PHY headers. Assuming 80 bytes/packet at the PHY layer, two packets are generated every second by each sensor node. Occasionally, packet sizes can be smaller resulting in higher packet rates and increased possibility of collisions with 802.15.4. Since efficient SHM typically requires quite dense sensor deployment, the packet losses may become even more considerable. As reported in [1] the average residence time for 1 packet in a multi-hop network of 10 sensors could be up to 142 secs. When this rate increases to 2 packets/sec per sensor, the network collapses.

The above factors result in considerable under-utilization of the sensor networks exploiting common data delivery techniques. Roughly speaking only 120 bytes/sec of the network bandwidth is utilized out of available 3750 bytes/sec. Meanwhile, a typical SHM application generates 200-600 bytes/sec of vibration data, which introduces an obvious performance bottleneck of existing WSNs for the SHM task.

3. WHIRLPOOL

The basic idea of whirlpool consists in splitting the sensor network into *sectors*, as illustrated in Figure 2, minimizing the number of packet collisions. The number and size of sectors can vary depending on the monitoring requirements. We define two sectors S1 and S2 as *colliding*, if at least one transmission of S1 collides with any transmission of S2. We assume that the adjacent sectors are always colliding. For example, in Figure 2b (S1, S2), (S1, S4), (S2, S3), and (S3, S4) are pairs of colliding sectors. Transmissions within a group of non-colliding sectors can be conducted concurrently except at the last hop as described below. This introduces natural *inter-sector concurrency*. In Figure 2b, the transmissions of (S1, S3) and (S2, S4) sector groups could be executed concurrently.

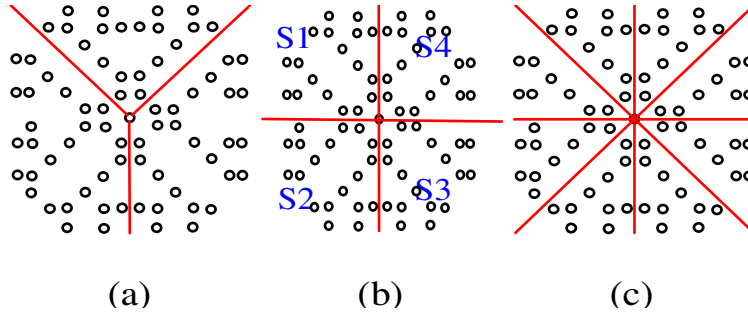


Figure 2: Sectoring of sensor network

Although some sectors can be scheduled concurrently, there is a one hop “serial bottleneck” near the whirlpool center, since all final elementary transmissions of each sector share the same destination (base station). Whirlpool algorithms that deal with this bottleneck are explained in [9]. Thus, whirlpool performs *rotating interrogation* in the sensor network. One whirlpool rotation is said to be *complete* if the base station receives a query response from each of the sectors. Multiple rotations constitute the case where responses from all the sectors are obtained two or more times.

In addition to the intra-sector concurrency, whirlpool also utilizes an *intra-sector concurrency*. We achieve this by combining whirlpool with our algebraic optimization framework that utilizes information about how the medium access control (MAC) layer operates while processing sensor queries [2]. The core component of the framework is Data Transmission Algebra (DTA) [2, 10]. The DTA consists of a set of operations that take transmissions between wireless sensor nodes as input and produce a schedule of transmissions as their output. We call an *elementary transmission* (denoted $ni \sim nj$) a one-hop transmission from sensor node ni to node nj . Each transmission $ni \sim nj$ is associated with a collision domain $CD(ni, nj)$, as defined in Section 2. A transmission schedule is either an elementary transmission or a composition of elementary transmissions using one of the operations of the DTA. The basic DTA includes three operations that combine two transmission schedules A and B:

- $o(\mathbf{A}, \mathbf{B})$. This is a strict order operation, that is, A must be executed before B.
- $a(\mathbf{A}, \mathbf{B})$. This is an overlap operation, that is, A and B can be executed concurrently.
- $c(\mathbf{A}, \mathbf{B})$. This is a non-strict order operation, that is, either A executes before B, or vice versa.

For example of DTA schedule consider a query tree in Figure 3 that corresponds to one sector of a whirlpool. The figure also shows the *initial DTA specification* reflecting basic constraints of the query tree. For instance, operation $a(n4 \sim n2, n5 \sim n3)$ specifies that $n4 \sim n2$ can be executed concurrently with $n5 \sim n3$, since neither $n3$ nor $n5$ belongs to $CD(n4, n2)$, and neither $n4$ nor $n2$ are in

CD($n5, n3$). The DTA includes a set of transformation rules [2] that can be used to generate complex transmission schedules. Figure 3 shows an example of a complete collision-free schedule that involves all elementary transmissions of the sector. Our optimizer performs cost based selection of the best schedule that maximizes the intra-sector concurrency [10].

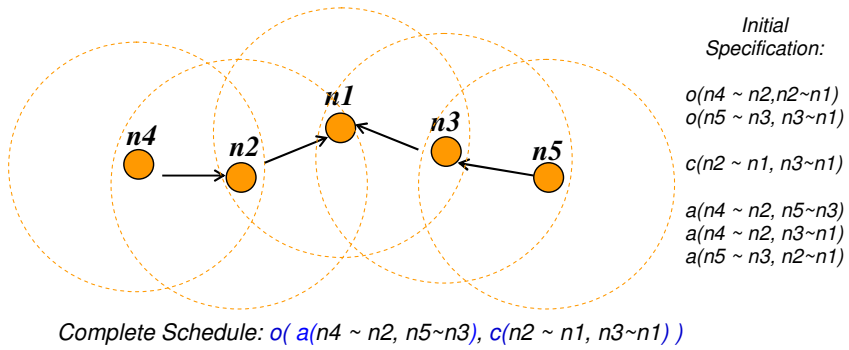


Figure 3: Example of DTA specifications

Our technique considerably increases the network utilization. For a nominal Zigbee data rate of 40 kbps the Whirlpool-based data transmission enables rates of up to 16 packets/sec. Figure 4 summarizes trends in time cost vs load in the sensor network for the traditional mechanisms (802.15.4 contention access (CAP) and guaranteed time slots (GTS)) and the Whirlpool technique. As the load increases, collisions increase especially with contention access. The use of GTS in 802.15.4 can alleviate it at least for transmissions that are to the same destination sensor. Collisions can still occur due to hidden terminals that are transmitting to other destination nodes. Whirlpool scheduling exploits concurrency and eliminates collisions providing the best performance.

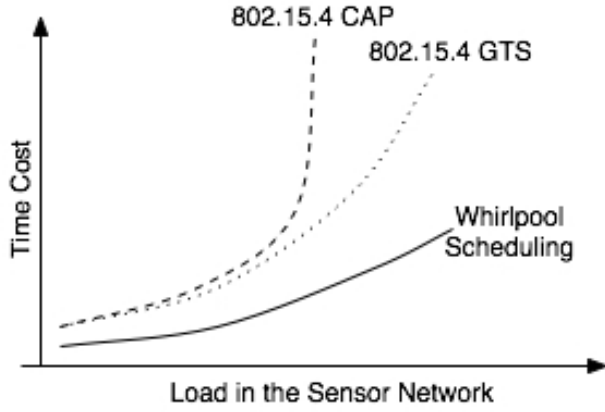


Figure 4: Time cost relationships between different scheduling schemas

4. DETECTING INSTABILITY USING WHIRLPOOL

In this section we illustrate the utility of the Whirlpool technique in the domain of non-intrusive SHM, - a procedure where the natural dynamics of a structure is observed for changes that indicate damage or instability. By quantifying these changes, the system may detect and locate the damage. Recently, progress has been made in using techniques from non-linear dynamics based on analysis of chaotic excitation signals in detecting structural instability. In general, structural behavior is considered as stable if observed structural parameters (e.g., vibration) are predictable, i.e., they are

either constant or periodic (Figures 5a and 5b). A structure qualifies for being unstable if its behavior is *chaotic*, i.e., if it exhibits a deterministic but non-predictable evolution (Figure 5c) [11, 12].

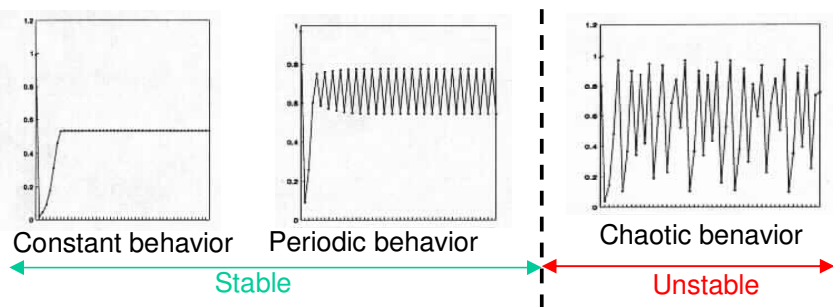


Figure 5: Data patterns for stable and unstable systems.

In order to detect chaotic behavior, a variety of measures have been used (e.g., Lyapunov exponent, Kolmogorov-Sinai entropy, etc.) [11]. We experimented with redundancy-based estimation of Kolmogorov-Sinai entropy and found it quite natural and efficient to detect chaotic behavior with WSNs. In this case, the data sample sensed by the sensors is time-shifted D times with a lag of m (D specifies the number of dimensions in the lag space). The resulting lagged time series $X_t, X_{t+m}, \dots, X_{t+(D-1)m}$ are compared with the original time-series for similarity that can be captured by information theoretical *redundancy measure* [11]. For stable data, the relation between redundancy and lag is a horizontal line at a constant ordinate value. For chaotic data, the plot gives us a downward sloping line. Figure 6 indicates beginning of instability at time moment 2000, where we observe a change in redundancy. Once a sample of data is received at the base station it is tested for redundancy with a suitable lag and a chosen embedding dimension.

Whirlpool can be effectively tuned to perform the instability detection as explained above. We assume that each sensor node accumulates a data sample every T_a seconds (*sample arrival rate*). The time interval from the beginning of transmission of a sample to the receipt of the sample at the base station is known as the *propagation delay* (T_p). As soon as a sample of data reaches the base station it can be analyzed to detect any indications of instability. Consider a simple Whirlpool structure and a plot of system-generated vibration data in Figure 7. First, the sensor nodes in one of the non-conflicting group of sectors, e.g. $\{1,1\}$, sample the vibration data (labeled by 1 in the vibration plot). Then, the collected data is transmitted to the base station that performs redundancy calculations. Note, that the system misses the readings that occur during the data propagation delay. When the second group $\{2,2\}$ is sensing and transmitting, the group $\{1,1\}$ stays idle and vice-versa. Thus, in this example the system is being interrogated twice per whirlpool rotation. Choosing specific Whirlpool sectoring and rotation speed we can control the propagation delay, sample size, data freshness and amount of missed data.

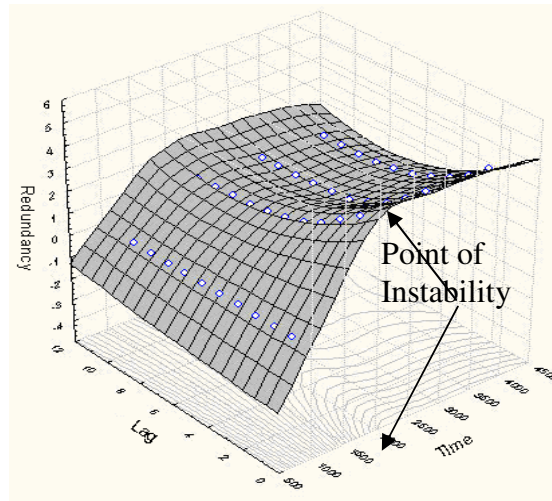


Figure 6: Incremental redundancy as indicator of system instability

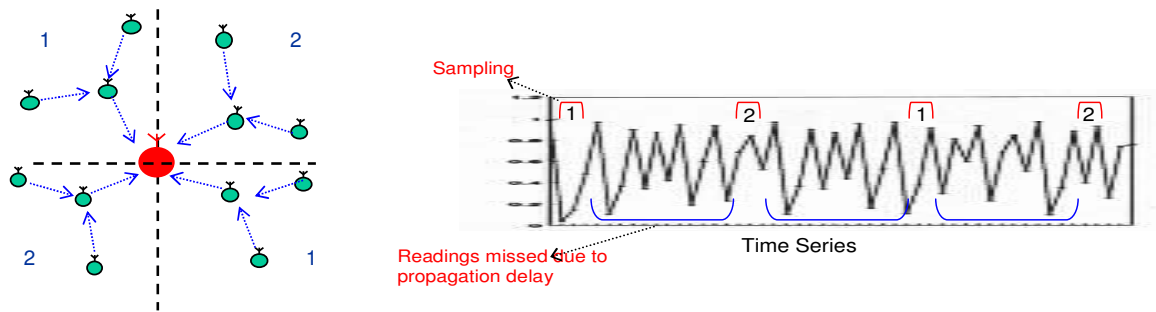


Figure 7: Simple Whirlpool for Instability Detection

The choice of specific sectoring and rotation speed also impacts the accuracy of instability detection. If the sample size is too large, instability will be detected with a considerable delay. Meanwhile, estimating redundancy on a smaller sampling interval typically results in less notable redundancy changes compared to larger sampling intervals. Smaller samples may provide not enough data for accurate redundancy estimates. This is illustrated in Figure 8. The left graph represents redundancy estimated on a sampling interval of 500, while the right redundancy graph corresponds to a sampling interval of 60. We observe step redundancy degradation for the larger sample and smooth redundancy change for the smaller sample. Although a smaller sampling interval may have a potential for providing more timely instability detection, it risks missing the instability due to redundancy miss-estimation.

Another problem may occur when a sample is collected in proximity of the unstable region. Case (a) in Figure 8 corresponds to a scenario where the sample includes both readings from stable and unstable system states. The amount of stable readings can hide the chaotic pattern of the unstable region during the redundancy estimation. This can result in a missed instability point. Similar situations may occur when the system returns to stable behavior after some instability period (case (b) in Figure 8). In this case, a false alarm may be raised. In order to handle the miss-estimations we introduce the concept of cut off accuracy of redundancy evaluation. If the redundancy change is greater than a heuristic value (*cut-off accuracy*) the system is reported as unstable. There are trade-offs in choosing the *cut-off accuracy*. If the cut-off accuracy is too small, almost every set of redundancies for given dimensions will qualify the system as unstable. If the cut-off accuracy is too

large, none of the data sets would detect instability. This further motivates Whirlpool tuning for optimal performance.

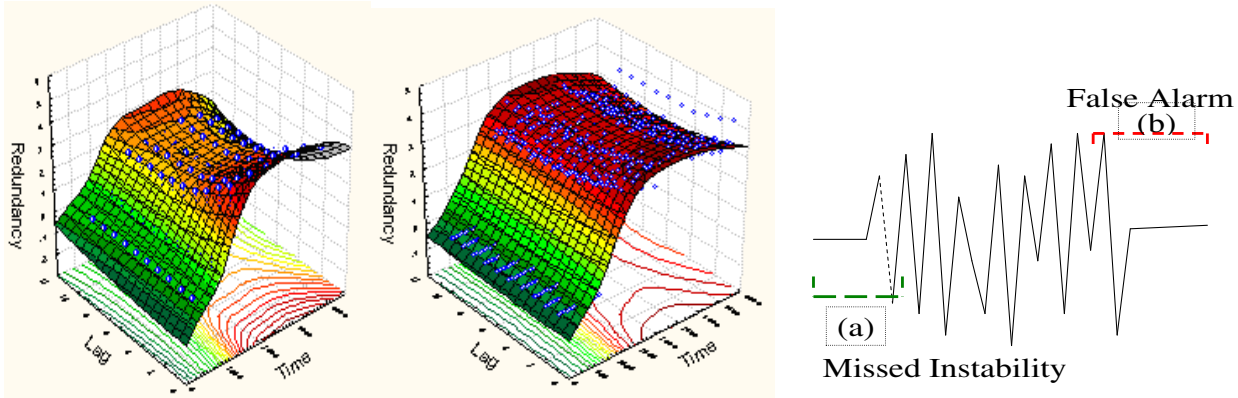


Figure 8: Effect of sampling on redundancy increment, missed instability and false alarms.

5. EXPERIMENTAL RESULTS

In this section, we provide some experimental results evaluating utility of the Whirlpool technique for the task of SHM. We configured a simulated sensor network with 75 sensors uniformly spread over a monitoring area. We simulated Zigbee WSN [13] with a frequency band of 915 MHz and a nominal data transmission rate of 40 kbps. We set the actual transmission rate at 30 kbps with a packet size of 120 bytes. We also generated several vibration time-series with patterns of instability. Figure 9 plots the instability detection time for different numbers of the Whirlpool sectors and sample sizes reflecting the Whirlpool rotation speed. We observe that, in general, instability is detected earlier with more number of sectors. Meanwhile, the overall Whirlpool performance slightly decreases as the number of sectors increases. The reason is that smaller and narrower sectors provide fewer opportunities for concurrent transmissions. We also observe that smaller sample size, which corresponds to faster Whirlpool rotation, allows Whirlpool to detect the instability earlier.

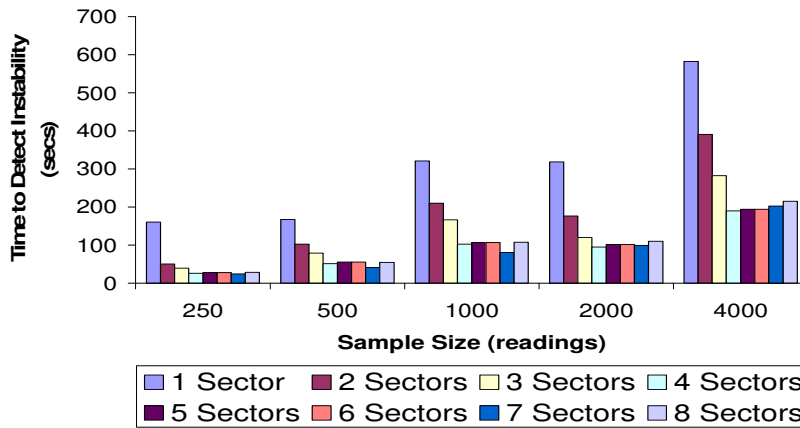


Figure 9: Instability detection time for different number of sectors at different sampling intervals

At the same time the Whirlpool tuned for smaller samples is more vulnerable to false and missed alarms, as explained in Section 4. This can be observed in Figure 10 that plots an average number of the false and missed alarms versus sample size. In general, an optimal choice of the sample size and cut-off accuracy is critical for accurate instability detection. From our experiments we found that a cut-off accuracy of 0.25 with sampling interval of 250 performs reasonably well.

6. CONCLUSION

We introduced a novel Whirlpool technique for scheduling and processing collision-free sensor queries for the task of Structural Health Monitoring. We demonstrated the efficiency of whirlpool in the domain of non-intrusive SHM, where a sensor network continuously examines the unique properties of output signals of the structure under critical integrity conditions.

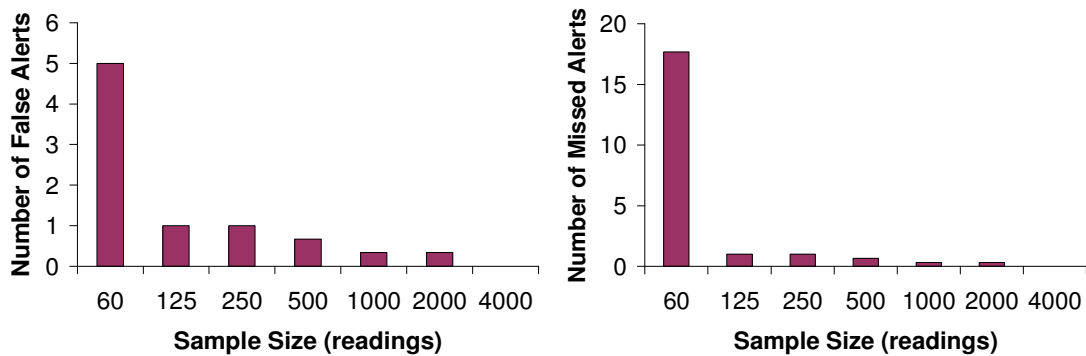


Figure 10: False and Missed Alerts

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REFERENCES

1. N. Xu, S. Rangwala, K.K. Chintalapudi, D. Ganesan, A Broad, R Govindan, and D Estrin, 2004. "A wireless sensor network for structural monitoring". *Proc. of the 2nd ACM Conference on Embedded Networked Sensor Systems*.
2. Zadorozhny, V., P. K. Chrysanthis, P.Krishnamurthy, 2004. "A Framework for Extending the Synergy between MAC Layer and Query Optimization in Sensor Networks". *Proc. of the International Workshop on Data Management for Sensor Networks. In conjunction with 30th International Conference on Very Large Data Bases*.
3. Johnson, E., H. Lam, L. Katafygiotis, J. Beck, 2004. "The Phase I IASC-ASCE Structural Health Monitoring Benchmark Problem using Simulated Data". *ASCE Journal of Engineering Mechanics*, 130(1).
4. Nichols, J., M. Todd, M. Seaver, L. Virgin, 2003. "Use of chaotic excitation and attractor property analysis in structural health monitoring". *Physical Review*.
5. Farrar, C.R., S.W. Doebling, and D.A. Nix., 2001. "Vibration-based structural damage identification". *Philosophical Transactions of the Royal Society of London: A – Mathematical, Physical and Engineering Sciences*,
6. IEEE Standard for Information technology - Local and metropolitan area networks: Part 11, June 1997. "Wireless Local Area Network Medium Access Control (MAC) and Physical Layer (PHY) Specifications".
7. IEEE Standard for Information technology - Local and metropolitan area networks: Part 15.4, October 2003: "Wireless Medium Access Control (MAC) and Physical Layer (PHY) Specifications for Low-Rate Wireless Personal Area Networks (LR-WPANs)".
8. Zheng, J., M. Lee, 2004. "Will IEEE 802.15.4 Make Ubiquitous Networking a Reality?: A Discussion on a Potential Low Power, Low Bit Rate Standard" *IEEE Communications Magazine*.
9. Sharma, D., V. Zadorozhny, P. Chrysanthis, 2005, "Timely Data Delivery in Sensor Networks Using Whirlpool". *To appear in Proceedings Proc. of the International Workshop on Data Management for Sensor Networks. In conjunction with 31st International Conference on Very Large Data Bases*.
10. Zadorozhny, V., D. Sharma, P.Krishnamurthy, A. Labrinidis, 2005. "Tuning query performance in sensor databases". *Proc. of 6th International Conference on Mobile Data Management*.
11. Williams, G.P., 1997. "Chaos Theory Tamed", *Joseph Henry Press*.
12. Abarbanel, H., 1996. "Analysis of Observed Chaotic Data". *Springer-Verlag*.
13. Zigbee Alliance Webpage, <http://www.zigbee.org>