Power-efficient wireless sensor reachback for SHM

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ABSTRACT: Wireless sensor networks have recently received great attention from the scientic community, because they hold the key to revolutionize many aspects of our economy and life. On the other hand, the design, implementation and operation of a wireless sensor network in a SHM system requires the synergy of many disciplines, including civil engineering, signal processing, networking, etc. The process of collecting the measurements acquired by a sensor network into a central sink node, constitutes one of the main challenges in this area of research and is often referred to as the sensor reachback problem. In this work, we describe a time-division multiple-access based protocol for sensor reachback, that takes into account the fact that sensor measurements are correlated in time and space, in order to reduce the amount of information that needs to be transmitted at the sink node. Furthermore, cooperative communication is incorporated into the developed protocol, so as to achieve reduced energy consumption. Experiments with real acceleration measurements, obtained from the Canton Tower in China during an earthquake, have demonstrated the effectiveness of the proposed method.

1 INTRODUCTION

Structural Health Monitoring (SHM) systems are widely adopted to monitor the behavior of structures during forced vibration testing or natural excitation (e.g. earthquakes, winds, live loading). Structural monitoring systems are applicable to a number of common structures including buildings, bridges, aircrafts and ships (Lynch 2006). Recent advances in microelectronics and wireless communications have enabled the development of low cost, low power devices that integrate sensing, processing and wireless communication capabilities. The collection of a large number of such devices, deployed over some territory of interest, gives rise to the so-called Wireless Sensor Network (WSN). Wireless sensor networks offer tremendous promise for accurate and continuous structural monitoring using a dense array of inexpensive sensors and possess many advantages over conventional wired systems, particularly for large civil infrastructure.

One of the most fundamental problems arising in such a network is related to the transmission of the acquired observations to a data-collecting node, often termed to as the sink node, which has increased processing and power consumption capabilities as compared to the sensor nodes. The sensor reachback problem, as it is usually called, has recently received considerable attention (Barros et al. 2004).

In general, there are several difficulties in the sensor reachback problem. Firstly, the amount of data generated by the sensor nodes is immense, owing to the fact that structural monitoring applications need to transfer relatively large amounts of dynamic response measurement data with sampling frequencies as high as 1000 Hz (Nagayama et al. 2010). Also, the number of sensor nodes may be very large. Next, the assumption that all sensors have direct, line-of-sight link to the sink does not hold in the case of these structures. Radio communication on and around structures made of concrete or steel components is usually complicated due to radio wave reflection, absorption, and other phenomena that result in poor received signal quality. Moreover, sensor nodes are frequently installed in partially- or completely- obscured areas, such as between girders. As a result, not all sensors may always have a channel to the sink of good enough quality and therefore, direct communication between each sensor node and the sink would consume all the energy stored in the batteries of the sensor nodes very quickly.

Hopefully however, recent advances promise that the aforementioned problems can be alleviated. Regarding the problem of massive data generated at the sensor nodes, it has been made clear that the fact that sensor readings from nearby sensors may be correlated, may be exploited so as to reduce the amount of information required to be transmitted to the sink node (Barros and Servetto 2006). For instance, the data collected by the sensors on each span of a bridge are correlated since they are measuring the vibration of the same part of the physical structure. In addition, in some cases of bridge design, two adjacent spans are connected to a common anchorage, resulting in the data across the two spans to be correlated. Similarly, in the case of large buildings, it is natural to group the sensors of the several distinct parts of the building (e.g. floors) and exploit their correlation. Thus, data compression approaches such as the Slepian-Wolf coding, implemented at the sensor nodes, offer the potential to greatly reduce the amount of information that needs to be transmitted (Stankovic et al. 2010). However, the Slepian-Wolf coding gives only information-theoretical bounds for data compression and it is quite difficult to be incorporated into a practical system.

Regarding the problem of the limited energy that the sensor nodes can afford for data transmission, recent advances in the field of cooperative communications promise to alleviate the problem.

In this work, we study a communication protocol that aims at overcoming the problems associated with sensor reachback. In particular, the spatial and temporal correlations among the measurements of the sensor nodes are exploited by employing an adaptive filter at each node that tries to predict the actual measurement using past measurements acquired from its neighbors. The sink node, keeps an exact replica of the filters that run on each sensor node. When a sensor node records a new measurement, it computes the prediction error. If the prediction error is small enough (i.e. below a predefined threshold) the node sends the output of its filter to its neighbors, so that they can use this value as input for the prediction filters they operate. In the opposite case, i.e., when the prediction error is not that small, the node updates its filter (i.e. using an adaptive algorithm such as the LMS or the RLS) and sends its actual measurement to its neighbors. In this case, the neighbors will transmit that measurement to the sink node in a cooperative fashion, using a 2 step procedure: At the first step, a number of collaborating sensor nodes exchange their data, whereas in the second step all the collaborating nodes simultaneously transmit to the sink node, thus forming a virtual Multiple Input Single Output (MISO) channel, which is known to result in energy savings as compared to the Single Input Single Output (SISO) case (Cui et al. 2004).

The new technique has been tested extensively via both simulated and real experimental data and it turns out that it may offer considerable savings in transmitted energy. Furthermore, the appropriate selection of cooperating sensor nodes is of great importance.

The remainder of this paper is organized as follows. In Section 2, the problem formulation is given. The proposed protocol is explained in more detail in Section 3 and possible extensions discussed. The results obtained by applying the protocol on real acceleration measurements from the Canton Tower in China during an earthquake are presented in Section 4. Section 5 concludes the paper.

2 FORMULATION OF THE PROBLEM

Let us consider a dense wireless sensor network consisting of N nodes, deployed in a civil structure that we wish to monitor. Consider also that node n ($n = 1, 2 \ldots, N$) has N_n neighbors, in the sense that they are close enough to node n so that wireless communication with low power can be accomplished. We will denote the neighbors of node n as $k_{n,1}, k_{n,2}, \ldots, k_{n,N_n}$. Each sensor node n, at discrete time t, acquires the measurement $y_{n,t}$ which is related to an event that takes place in the area where the wireless sensor network has been deployed. Define also the vectors of m past measurements of each sensor node n as

$$\mathbf{y}_{n,t} = [\; y_{n,t-1} \quad y_{n,t-2} \quad \cdots \quad y_{n,t-m} \;]^T \;, \qquad n = 1, 2, \ldots, N \;. \tag{1}$$

Also, let us define the stacked vectors

$$\mathbf{u}_{n,t} = \left[\; \mathbf{y}_{n,t}^T \quad \mathbf{y}_{k_{n,1},t}^T \quad \mathbf{y}_{k_{n,2},t}^T \cdots \quad \mathbf{y}_{k_{n,N_n},t}^T \;\right]^T \;, \qquad n = 1, 2, \ldots, N \;, \tag{2}$$

that represent the past m measurements of all sensor nodes in the neighborhood of node n. Consider now the correlation matrices defined as

$$\mathbf{R}_n = E[\mathbf{u}_{n,t}\mathbf{u}_{n,t}^T] \;, \qquad n = 1, 2, \ldots, N \;. \tag{3}$$

Clearly, if the matrices $\mathbf{R}_n$ are diagonal, the sensor measurements within all neighborhoods are uncorrelated. In contrast, if the matrices $\mathbf{R}_n$ are only block-diagonal with block size m, the measurements are correlated in time but spatially uncorrelated. In this work, we will focus on the general case where $\mathbf{R}_n$ are of a general form, implying that the sensor measurements are correlated both in time and in space.

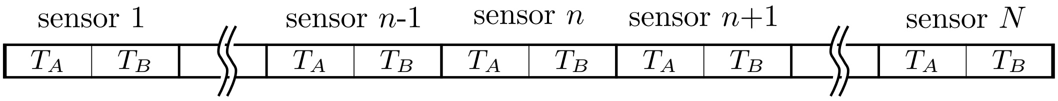

Figure 1: Each of the sensors is assigned its own time-slot to transmit, in a TDMA fashion. Furthermore, each time-slot is divided into two sub-slots. During the first sub-slot of duration T_A, each sensor n transmits to its k_n neighbors. During the second sub-slot of duration T_B, node n and its neighbors transmit to the sink node in a cooperative fashion.

3 A TDMA BASED COOPERATIVE PROTOCOL

3.1 *Predictors and correlation of measurements*

Due to the nature of the observed phenomenon the measurements' process $y_{n,t}$ is commonly a predictable one, at least to some extent. Assuming the process to be stationary, the predictor can be realized as a linear filter with optimal coefficients obtained by minimizing the mean-squared error between the measurement $y_{n,t}$ and its predicted value.

However, in most real world applications the observation processes are non-stationary since their statistical characteristics are changing in time. As a result, the optimal coefficients of the predictor are changing in time as well. In order to track these changes, a practical approach is to iteratively calculate them by updating previous filter coefficients as it is done in adaptive filters (Sayed 2008).

In this work, it is also of interest to consider the dependence among the processes of acquiring measurements in a certain neighborhood of node n. Accordingly, the prediction filter at node n should provide the predicted value of an actual measurement taking into account its own past measurements as well as the past measurements of other nodes to which node n is spatially correlated with.

3.2 *Simple cooperative TDMA protocol*

Let us consider now a straightforward cooperative communication protocol for the problem at hand, in which correlation among the measurements acquired by the nodes of the WSN is not taken into account. According to this protocol, each sensor node is assigned its own time-slot in order to transmit information, in a Time Division Multiple Access (TDMA) fashion. Cooperative communication can be incorporated into this protocol, by dividing each time-slot into two sub-slots as depicted in Figure 1. During the first sub-slot of duration T_A, each sensor n transmits its estimated (or observed) value to its k_n neighbors. During the second sub-slot of duration T_B, node n and its neighbors transmit to the sink node in a cooperative fashion. In such a scenario, both the Amplify and Forward (AF) as well as the Decode and Forward (DF) methods (Hong et al. 2007) can be adopted.

3.3 *Cooperative TDMA exploiting correlation*

Consider now an extension of the aforementioned protocol, where the correlation of the measurements is taken into account. Since the measurements are correlated in time and in space, the idea of using past measurements from nearby sensor nodes in order to predict new measurements seems well justified. This fact can be used to save some of the transmissions to the sink node, in the case where the sink node can itself predict the required measurements within some predefined accuracy. Thus, let each sensor node n keep a time varying prediction filter $\mathbf{f}_{n,t}$ as well as a data vector

$$\tilde{\mathbf{u}}_{n,t} = \left[\begin{array}{cccc} \tilde{\mathbf{y}}_{n,t}^T & \tilde{\mathbf{y}}_{k_{n,1},t}^T & \tilde{\mathbf{y}}_{k_{n,2},t}^T \cdots & \tilde{\mathbf{y}}_{k_{n,N_n},t}^T \end{array} \right]^T , \qquad (4)$$

so that the output of the filter, defined as

$$\hat{y}_{n,t} = \mathbf{f}_{n,t}^T \cdot \tilde{\mathbf{u}}_{n,t} \qquad (5)$$

is an approximation of the actual measurement $y_{n,t}$ obtained by sensor n at time t. In the above expressions, we have used the vectors

$$\begin{aligned} \tilde{\mathbf{y}}_{n,t} &= [\ \tilde{y}_{n,t-1} \quad \tilde{y}_{n,t-2} \quad \cdots \quad \tilde{y}_{n,t-m}\ ]^T , \\ & n = 1, 2, \ldots, N . \end{aligned} \qquad (6)$$

to represent approximate versions of the past m measurements obtained by sensor n. Thus, vectors $\tilde{\mathbf{u}}_{n,t}$ and $\mathbf{f}_{n,t}$ have dimensions $m \cdot k_n \times 1$. Let us now define a binary variable $b_{n,t}$ according to the prediction error, as

$$b_{n,t} = \begin{cases} 0 & \text{if} \quad |\hat{y}_{n,t} - y_{n,t}| \leq e \\ 1 & \text{if} \quad |\hat{y}_{n,t} - y_{n,t}| > e \end{cases} , \qquad (7)$$

where e denotes a small positive constant. The approximate measurements $\tilde{y}_{n,t}$ are defined as,

$$\tilde{y}_{n,t} = \begin{cases} \hat{y}_{n,t} & \text{if} \quad b_{n,t} = 0 \\ y_{n,t} & \text{if} \quad b_{n,t} = 1 \end{cases} . \qquad (8)$$

Based on the above definitions, the protocol of each sensor node n can be seen in Table 1. At a time instant t, each sensor acquires its new measurement $y_{n,t}$ and starts a synchronized loop to track the N time-slots that will follow. As seen from Table 1, node n is active in two cases: (a) When the current slot s is equal to its index n, and (b) when the current slot s is equal to the index of any of its neighbors. In case (a), the node computes the output of its prediction filter and compares it to the actual measurement $y_{n,t}$. Thus, it computes the binary variable $b_{n,t}$ that determines whether the prediction was accurate or not. In

Table 1: The protocol executed by the sensor node n

```
Initialize f_{n,0}, ũ_{n,0} and e
For t = 0 to +∞
  Acquire the measurement y_{n,t}
  For s = 1 to N
    If s = n then
      ŷ_{n,t} = f_{n,t}^T ũ_{n,t}
      b_{n,t} = { 0  if  |ŷ_{n,t} − y_{n,t}| ≤ e
                { 1  if  |ŷ_{n,t} − y_{n,t}| > e
      ỹ_{n,t} = { ŷ_{n,t}  if  b_{n,t} = 0
                { y_{n,t}  if  b_{n,t} = 1
      If b_{n,t} = 1
        Update the prediction filter to f_{n,t+1} (use y_{n,t})
      End
      Update ũ_{n,t+1} using ỹ_{n,t}
      Send ỹ_{n,t} and b_{n,t} to the neighbors (T_A sub-slot)
      If b_{n,t} = 1
        Send ỹ_{n,t} to the sink (T_B sub-slot)
      End
    Elseif s ∈ {k_{n,1}, k_{n,2}, ..., k_{n,N_n}}
      Listen for ỹ_{s,t} and b_{s,t} (T_A sub-slot)
      Update ũ_{n,t+1} using ỹ_{s,t}
      If b_{s,t} = 1
        Send ỹ_{s,t} to the sink (T_B sub-slot)
      End
    Else
      Sleep(T_A + T_B seconds)
    End
  End
End
```

Table 2: The protocol executed by the sink node

```
Initialize f_{n,0}^{(S)}, ũ_{n,0}^{(S)} (n = 1, 2, ..., N)
For t = 0 to +∞
  For s = 1 to N
    Sleep(T_A seconds)
    Listen for ỹ_{s,t} (T_B sub-slot)
    b̂_{s,t} = { 0  if  ỹ_{s,t}  was not detected
              { 1  if  ỹ_{s,t}  was detected
    If b̂_{s,t} = 0
      ỹ_{s,t}^{(S)} = f_{s,t}^{(S)T} ũ_{s,t}^{(S)}
    Else
      ỹ_{s,t}^{(S)} = ỹ_{s,t}
      Update the prediction filter to f_{s,t+1}^{(S)} (use ỹ_{s,t})
    End
    Update ũ_{s,t+1}^{(S)} using ỹ_{s,t}^{(S)}
    For i=1 to N_s
      Update ũ_{k_{s,i},t+1} using ỹ_{s,t}^{(S)}
    End
  End
End
```

the case where the prediction was not accurate, the prediction filter is updated using an adaptive algorithm (such as the LMS or the RLS), and the value $y_{n,t}$ as desired response. The sensor then computes $\tilde{y}_{n,t}$, which is either the output of the prediction filter (accurate prediction) or the actual measurement (inaccurate prediction). Thus, sensor n updates its input vector $\tilde{\mathbf{u}}_{n,t+1}$ and sends $\tilde{y}_{n,t}$ and $b_{n,t}$ to its neighbors. Finally, $\tilde{y}_{n,t}$ is sent to the sink node only if the prediction was inaccurate, otherwise the sink node is able to compute $\tilde{y}_{n,t}$ using a prediction filter. In case (b), i.e. when a neighbor of n is active, node n listens for the transmitted values $\tilde{y}_{s,t}$ and $b_{s,t}$. It then updates its input vector $\tilde{\mathbf{u}}_{n,t+1}$ with the received value $\tilde{y}_{s,t}$ and, in the sequel, helps its neighbor transmit to the sink by relaying $\tilde{y}_{s,t}$ if $b_{s,t}$ was 1.

The protocol followed by the sink node is depicted in Table 2. At each time instant, the sink node also executes a loop so as to track the N time-slots, in a synchronized fashion. For the first T_A seconds of each slot, the sink node is inactive because sensor-to-sensor communication takes place. At the following T_B seconds however, the sink node is receiving the measurement $\tilde{y}_{s,t}$ of the node assigned to the current slot. Of course, in the case where the prediction at node s was accurate, such a message will not be transmitted. Thus, the sink node must implement a procedure to detect such "empty" messages. The result of the detection process is a binary variable $\hat{b}_{s,t}$ which will be equal to $b_{s,t}$ in the case where the detection is correct. In the sequel, the sink node is able to compute $\tilde{y}_{s,t}^{(S)}$, (that is, a copy of $\tilde{y}_{s,t}$ at the sink) either as the output of a local prediction filter, i.e.,

$$\tilde{y}_{s,t}^{(S)} = \mathbf{f}_{s,t}^{(S)^T} \cdot \tilde{\mathbf{u}}_{s,t}^{(S)} \ , \tag{9}$$

in the case where $\hat{b}_{s,t} = 0$ (accurate prediction) or by setting it equal to the received measurement $\tilde{y}_{s,t}$ (inaccurate prediction). In the case of inaccurate prediction, the sink node must use the same adaptive algorithm as the sensor s to update its local prediction filter for sensor s, so that the two filters are equal (of course, if all channels are error free). Finally, the sink node must update the input vectors of all the prediction filters affected by $\tilde{y}_{s,t}$, that is the prediction filter for node s and the local prediction filters of all its neighbors.

It can be verified by the above, that in the case where all channels are error-free, the reconstructed sequences $\tilde{y}_{n,t}^{(S)}$ at the sink node satisfy the distortion criterion

$$\max_{n,t} |\tilde{y}_{n,t}^{(S)} - y_{n,t}| \leq e \ . \tag{10}$$

3.4 *Possible extensions*

In the previous sub-sections the basic version of the new method was presented. The method can be extended to several directions with relative pros and cons. Below we provide some brief discussion of possible extensions. The corresponding techniques are currently under investigation.

1) In the proposed protocol, in case that the predicted value is not accurate enough, the node transmits the real measurement to the sink. However, since the sink has an exact replica of the filter that run on each sensor node, it may calculate the inaccurate predicted value by itself, as previously explained in Section 3.3. Some power can be saved by sending only

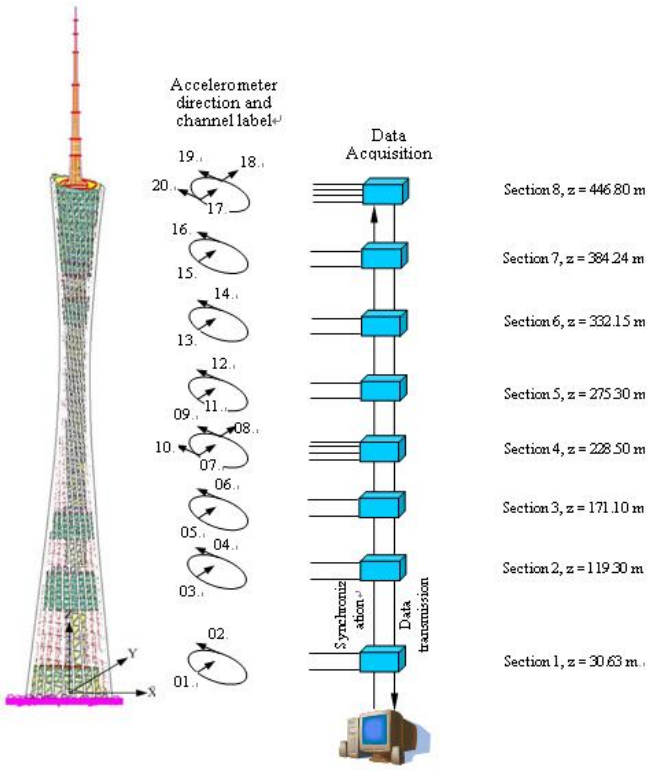

Figure 2: The distribution of accelerometers along the tower height

this difference (the prediction error) instead of the whole measurement.

The actual measurement and its predicted value are highly correlated, so their difference has small variations and, therefore, in order to achieve a given distortion fewer bits are required.

It is well-known by basic Rate-Distortion Theory (Proakis and Salehi 2001) that for a zero-mean Gaussian source with variance σ^2 and with squared-error distortion measure D, the rate-distortion function is given by

$$R(D) = \begin{cases} \frac{1}{2}log(\frac{\sigma^2}{D}) & 0 \leq D \leq \sigma^2 \\ 0 & \text{otherwise} \end{cases} . \tag{11}$$

Assuming that the prediction error and the measurement signal are zero-mean Gaussian sources, for a given distortion $D \leq \sigma_e$, it can be easily shown that

$$R_e = R_y - \frac{1}{2}log(\frac{\sigma_y^2}{\sigma_e^2}) , \tag{12}$$

where R_e, R_y represent required bits to send the prediction error and the measurement signal, respectively, while σ_e^2, σ_y^2 are their variances.

This means that this modified protocol can achieve performance levels compared to the original at lower bit rates when the prediction errors are relatively small. The gain is expressed as the second term in (Eq. 12). However, providing the exact relation of this gain to the distortion criterium is not straightforward due to the following. Firstly, the distortion value influences the process of adaptive filtering and thus influences the prediction error and its variance. Secondly, only the prediction errors greater than specific distortion value are being transmitted which results in variance change of transmitted sequence comparing to the variance of the sequence of all prediction errors.

Let us provide an example of a possible gain using the measurements described in Section 4.2. In case that sensor 10 cooperates with sensors 9 and 4, and for the distortion value corresponding to sending the measurement with 8 bits (R_y =8 bits), the gain defined in Equation 12 equals to 4.1285 bits. Accordingly, 50% of power could be saved by sending only the prediction error (R_e =4 bits) instead of the measurement in this case.

2) Another approach to improving the protocol described in Section 3.3 could be to use only appropriately chosen delayed samples of a cooperating neighbor and not all samples in between. For instance, the highest cross-correlation between the measurements of nodes 2 and 4 arises for $delay = 45$. Therefore, it can be concluded that the adaptive predictor could have significantly less coefficients and still to be able to exploit the spatial correlation of a great delay. In order to optimize the performance of this protocol, some training period should be performed during forced vibration testing.

3) Finally, the protocol can be improved by allowing each sensor to update its own filter with the real measurement regardless of distortion criteria, but still to send the measurements to the sink and to also periodically send the filter coefficients to the sink only if the prediction was inaccurate (i.e., large change in input signal). In this scenario, the filter at the sink node has slightly worse prediction abilities. Hence, it is necessary to periodically receive the filter coeffi-

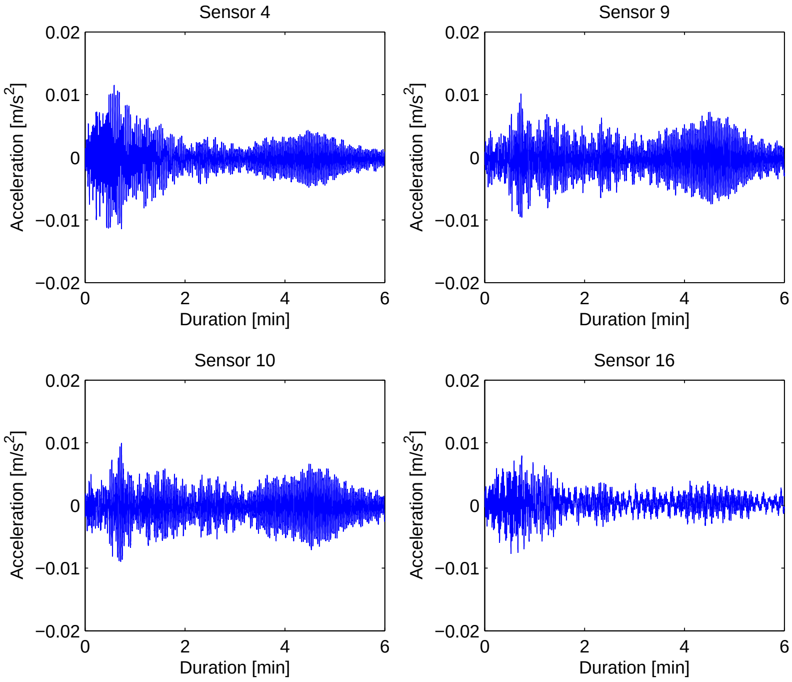

Figure 3: The measured acceleration data sequences

cients changes from the sensor node in order to adjust its own filter and satisfy the distortion criterion.

4 NUMERICAL RESULTS

Extensive experiments with both simulated and real data have demonstrated the effectiveness of the proposed method. In this section we present only some indicative experimental results with real data since we consider they are of more interest to the SHM community. More specifically, the real acceleration measurements from the Canton Tower obtained during an earthquake have been used in order to present different gains of cooperation among the nodes.

4.1 *The Canton Tower*

The Canton Tower (the Guangzhou TV and Sightseeing Tower) was constructed in 2010 in Guangzhou, China. It has already attracted the interest of several researchers (Casciati et al. 2009). It is a supertall structure with a height of 610m. On the top level of the tower at height of 454m an antennary mast is mounted with 164m height (Fig. 2).

The tower is a tube-in-tube structure; the outer tube is made of steel and the inner one is a reinforced concrete tube. The two tubes are linked together by 36 floors and 4 levels of connection girders. The underground part of the tower is 10m height and consists of 2 floors with plan dimensions of 167m by 176m. The outer tube is shaped by concrete-filled-tube (CFT) columns, spaced in an oval shape, inclined vertically, and connected by hollow steel rings and braces. The oval shape dimensions varies from 60m by 80m at the underground level (altitude of -10m) to their minimum values of 20.65m by 27.5m at the altitude of 280m, and then they increase again to 40.5m by 54m at the top level of the tube (altitude of 450m). The oval shape of the top level is rotated 45 degrees horizontally relative to that of the bottom level. The top level plan is also inclined 15.5 degrees to the horizontal plane. The inner tube shape is an oval with constant dimensions along its height (14 m by 17 m), and its centroid is not that of the outer tube. The thickness of the tube varies from 1m at the bottom to 0.4m at the top (Ni et al. 2009).

A SHM system consisting of over 600 sensors has been designed and implemented by the Hong Kong Polytechnic University for both in-construction and in-service real-time monitoring of the tower (Benchmark 2008). The distribution of accelerometers along the tower height is demonstrated in Figure 2. The dynamical response of the tower to an earthquake was recorded by 17 sensors. The measured acceleration data sequences obtained from several sensors are illustrated in Figure 3 for six minutes of response during an earthquake. The sampling frequency of the signal was 50 Hz.

4.2 *Results*

In order to illustrate the gain achieved by applying the protocol, we examine the number of transmissions toward the sink from a specific node as a function of some distortion. For a given distortion, the number of required transmissions from a certain node toward the sink varies with reference to which node(s) are selected for cooperation.

In Figure 4, a performance comparison for sensor

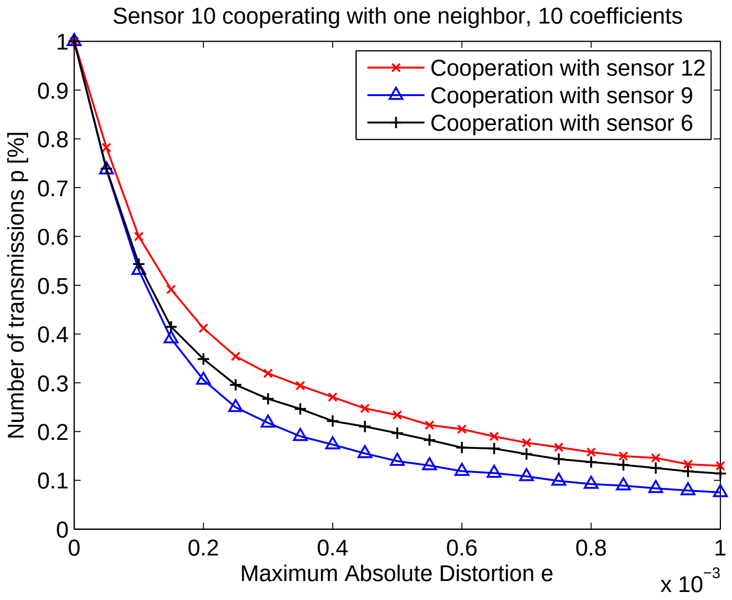

Figure 4: Sensor 10 cooperating with one neighbor

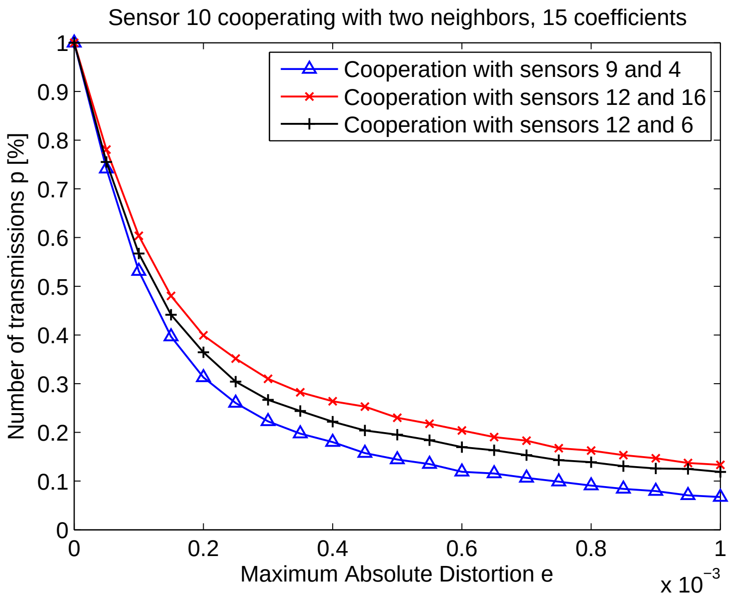

Figure 5: Sensor 10 cooperating with two neighbors

node 10 cooperating with a single neighbor is given. It is clear that the best performance, in terms of power saving, is achieved when node 10 cooperates with node 9, which is rather expected since both sensors are on the same floor (Fig. 2).

Figure 5 presents a performance comparison when sensor node 10 cooperates with two neighbors. Cooperation with sensor nodes 9 and 4 gives better performance compared to the case when it cooperates with sensor nodes 12 and 6 and sensor nodes 12 and 16.

Therefore, exploiting spatio-temporal correlations reduces power consumption of a sensor node. Furthermore, finding an optimal cooperating neighborhood can be of great significance.

5 CONCLUSIONS AND FURTHER WORK

A TDMA based protocol for sensor reachback in a SHM system has been described. The proposed protocol, takes into account the fact that sensor measurements are correlated in space and time in order to reduce the amount of information bits needed to transmit the measurements acquired by the sensor nodes back to a sink node, within some prescribed distortion e. Also, the protocol does not need to know the statistics of the event being monitored by the wireless sensor network, rather, these statistics are learned via the use of adaptive algorithms. Furthermore, the protocol uses the idea of cooperative communication in order to reduce the required transmission power. The new technique has been tested extensively via real experimental data and it turns out that it may offer considerable saving in transmitted energy. Furthermore, the appropriate selection of cooperating sensor nodes is of great importance.

ACKNOWLEDGEMENTS

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