Interleaving Wavelet Coefficients for Adaptive Data Transmission from Pervasive Sensing Systems

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***Abstract*—The paper describes a method for adaptive transmission of data over error-prone wireless links and suited to the limitations of embedded pervasive sensing systems. The technique performs a multiresolution wavelet transform on the data followed by interleaving the resulting coefficients among the transmitted packets. The interleaving scheme is designed to facilitate estimation of coefficients lost during transmission by minimizing the correlation between elements in one packet. A correlation model between detail coefficients obtained from a wavelet transform of Gauss-Markov processes is used to estimate the optimal distribution of coefficients to packets. The interleaving ensures that packet loss results in noncontiguous "gaps" in the reconstructed wavelet tree. The original data is reconstructed by polynomial interpolation of the missing coefficients from correlated neighboring coefficient. We present simulation results that show the performance of our scheme on both real-world and simulated datasets.**

I. INTRODUCTION

Pervasive sensor-based systems (such as wearable health monitoring systems) typically transmit sensor data over wireless links. However, radio transmission is prone to interference. A data stream from a sensor is quantized into packets before wireless transmission and interference results in dropped packets. The two common schemes for reliable transmission over a noisy channel are Forward Error Correction (FEC) and Automatic Repeat Request (ARQ). However, these methods assume that the communicating nodes either have sufficient computational power to calculate the redundant bits or the energy resources to engage in retransmissions. The computational and energy resources available to embedded systems are extremely limited [1]. Thus, the error correction schemes designed for general purpose wireless communication are less suitable for data transmission from embedded systems.

In this work, we describe a data transmission strategy that is tailored to the specific requirements and constraints of a class of embedded systems for pervasive sensing. Such systems are expected to continually sense their environment for extended periods before exhausting their internal power supply. In most such applications, it is sufficient to monitor the environment at a nominal level and escalate the sensing only during times of abnormal activity. Ideally, the transmission scheme 1) should not add significant overhead to the packet load, 2) must not require a computationally intensive algorithm to be executed at the transmitter or reciever, and 3) adapt the fidelity of the transmitted data to the application requirements. The first two requirements are due to the limited computational and energy resources available to embedded systems. The third requirement enables the embedded system to conserve resources through adaptive sensing.

Our main contribution is a data transmission method that addresses these requirements. The method transmits a multiresolution representation of the data using a novel packetization and interpolation scheme. Compressing large volumes of data prior to transmission conserves power and bandwidth. We have chosen the discrete wavelet transform as the basis for the compression step. Sensor data is then transmitted in the form of their component wavelet coefficients. The wavelet transform enables the data to be compressed to varying extents, enabling the system to adapt its compression level (and thus data fidelity) to the application needs.

The loss of packets results in "gaps" in the reconstructed data at the receiver. Rearranging the original order ensures that the loss of a contiguous portion of the transmitted data from packet drops only results in the loss of multiple non-contiguous segments of the original data. Since most naturally occurring data have structure and correlation across time/space, these missing non-contiguous portions can be approximated from their neighboring segments. However, interleaving after a transformation is dependent on the correlation model in the transformed domain. In this paper, we describe an algorithm to interleave wavelet coefficients among transmission packets that is based on the statistical relationship between wavelet coefficients across both scale and time/space. The interleaving algorithm minimizes the total correlation between coefficients within every packet. Every coefficient in a packet will then have correlated coefficients in other packets. We also present a polynomial interpolation algorithm between wavelet coefficients to approximate missing coefficients at the receiver. In case a packet gets dropped during transmission, all coefficients in that packet can be approximated by applying our interpolation algorithm to neighboring coefficients. The interleaving scheme is computed offline before deployment and only the final packetization pattern is stored at each node. Thus, the computational requirements of our scheme are minimal as compared to FEC. The steps of this process are depicted in Figure 1.

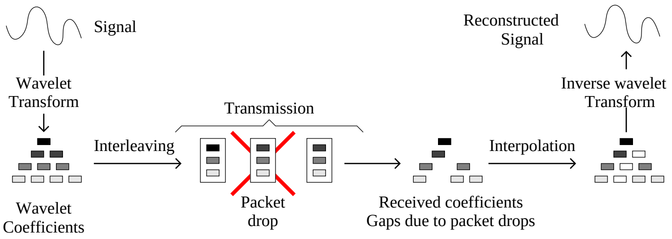


Fig. 1. Block diagram of the data transmission scheme

This work is motivated by the requirements of the autonomous long-term health monitoring system being developed at the Childrens Hospital of Los Angeles [2], [3], [4]. Biomedical sensors attached to the human body are connected to motes which then communicate with a central handheld computer periodcally over a wireless link. This central computer regulates the sensing parameters (sampling rates, compressions) of the individual sensors to ensure critical events are adequately sensed. Thus, the ability to transmit data between nodes in an efficient and adaptable manner is crucial to this application.

II. RELATED WORK

Adaptive sensing is implemented for a river monitoring application in [5]; only components useful for determining water level are transmitted from the sensor. [6] describes a method of interpolating missing Discrete Cosine Transform (DCT) coefficients of images. Linear interpolation of the corresponding coefficients in adjacent image blocks is used to approximate the missing coefficients. [7] presents an interleaving pattern for the DCT coefficients obtained from an image. In that work, coefficients are distributed so that adjacent DCT blocks do not contain the same frequency components. Lost coefficients are then interpolated from the adjacent spatial blocks. In contrast, we use the wavelet transform in our transmission scheme to facilitate interpolation. [8] describes a distributed data compression scheme for sensor networks, but the effects of packet loss are not considered. The varying spatial resolution in the wavelet transform retains some of the spatial correlation in the original signal, unlike in the case of the DCT transform. Cheung and Po interleave integer wavelet coefficients in their image coding algorithm to exploit correlation between coefficients [9]. However, the interleaving pattern is not based on a correlation model arising from a stochastic data model. Xu et al. use integer wavelets for compression in a sensor network [10]. In their work, the interleaving of wavelet coefficients was not explored. [11] describe a method that uses both bit-level interleaving and FEC to reduce the effect of burst errors in Bluetooth wireless networks. That work differs from the interleaving scheme presented here in that their work focuses on bit errors *within* a packet.

The correlation measures used in this work are based on Gauss-Markov processes [12]. In the case of fractional Brownian motion processes, the correlation between the discrete wavelet coefficients decreases exponentially across levels and hyperbolically across time [13]. An alternate representation of the statistical dependency between wavelet coefficients is described in [14]. That work uses Hidden Markov Models and Gaussian mixture models to represent the distribution of wavelet coefficients. The correlation between coefficients has been exploited for different purposes such as image denoising [15] and lossless image compression [9]. For image compression, the correlation between coefficients obtained from an integer wavelet transform was used [9].

III. INTERLEAVING COEFFICIENTS IN PACKETS

In a multi-level wavelet transformation, the signal is split into its low frequency and high frequency components. These components are represented by the coefficients of the wavelets that together represent the parent signal. The coefficients that form the low frequency component are called *approximate* coefficients and those that form the high frequency component are called *detail* coefficients. The low frequency component (approximate coefficients) is recursively split further into two frequency bands until the set of approximate coefficients cannot be further reduced. The coefficients that represent the decomposed signal are at the leaves of this decomposition tree. These coefficients are then used to reconstruct the original signal. Note that the number of coefficients at coarser levels are fewer in number than at the finer levels.

The correlation between detail coefficients obtained from a multi-level wavelet decomposition of a Gauss-Markov process decays exponentially with both time (space) and level (granularity of decomposition) [12]. A Gauss-Markov process $X(t)$ is a stochastic process defined by the differential equation

$$dX(t) = -\frac{1}{2}\alpha X(t)dt + dW(t)$$

where W(t) is Brownian motion and $\alpha > 0$ [12].

Let C be the set of N detail coefficients obtained from the wavelet decomposition of the signal to be transmitted. Denote by $l(c)$ and $t(c)$ the level and time respectively of coefficient $c \in C$. Then, the correlation $r(c_i, c_j)$ between coefficients c_i and c_j, $l(c_i) > l(c_j)$, is given by [12]:

$$r(c_i, c_j) \leq$$

$$\begin{cases} K_1 e^{-\alpha(2^{l(c_i)}t(c_i) - 2^{l(c_j)}t(c_j) - M(2^{l(c_i)} + 2^{l(c_j)}))}, \\ \quad \text{for } 2^{l(c_i)}t(c_i) - 2^{l(c_j)}t(c_j) > M(2^{l(c_i)} + 2^{l(c_j)}) \\ K_1 e^{-\alpha(2^{l(c_i)}t(c_i) - 2^{l(c_j)}t(c_j) - M(3\times 2^{l(c_i)} + 2^{l(c_j)}))}, \\ \quad \text{for } 2^{l(c_i)}t(c_i) - 2^{l(c_j)}t(c_j) \leq -M(3 \times 2^{l(c_i)} + 2^{l(c_j)}) \\ K_2 2^{-\frac{l(c_i) - l(c_j)}{2}}, \\ \quad \text{otherwise} \end{cases}$$

where

$$K_1 = 2M||\psi||_\infty ||\phi||_\infty \frac{1}{2^{l(c_j)}\alpha^2} 2^{-\frac{l(c_i) - l(c_j)}{2}}$$

$$\begin{aligned} K_2 =& 2M||\psi||_\infty ||\phi||_\infty 2^{l(c_j)} \times \\ & \left[(4M)^2 + \frac{4}{\alpha 2^l(c_j)} (\frac{1}{\alpha 2^l(c_j)} + 1) \right] \end{aligned}$$

ψ is the wavelet function, $2M$ is the length of the wavelet support, and ϕ is the corresponding scaling function. These are constant for a particular choice of wavelet transform.

The N coefficients are to be distributed into P packets. Let the maximum number of coefficients that can be transmitted in a packet p be N_p and $\sum_{p=1}^{P} N_p \geq N$. An *assignment* A is a mapping from the set of coefficients to packets. $A(c) = p$ denotes that coefficient c is to be transmitted in packet p under assignment scheme A. We define the correlation of a coefficient c within a packet p under assignment A as the maximum correlation between c and every other coefficient in packet p:

$$r_A(p, c) = \max(r(c, c_i)), c_i \in C, A(c_i) = p$$

The total correlation in a packet p, $r_A(p)$ is now defined as the sum of individual correlations within packet p:

$$r_A(p) = \sum_{c \in C, A(c)=p} r_A(p, c)$$

The total correlation induced by assignment A, r_A, is the sum of all the packet correlations:

$$r_A = \sum_{p=1}^{P} r_A(p)$$

We then select the interleaving scheme, A^*, that distributes coefficients such that the total correlation in the packets, r_{A^*}, is minimal over all possible interleaving schemes.

A. Greedy algorithm to calculate interleaving pattern

We conjecture that the problem of determining the optimal assignment as defined above is NP-Complete due to its similarities with the bin packing problem [16]. Thus, the optimal assignment can be found only by performing a brute-force search over the space of all possible assignments. As the number of such assignments grows exponentially with N and P, this method is infeasible even for moderate number of coefficients. We instead find sub-optimal solutions using a greedy approach (Figure 2) that assigns coefficients to packets such that the correlation with the previously assigned coefficients is minimized. Initially, one of the coefficients is added to one packet. At every subsequent step of the algorithm, we add every unassigned coefficient to each available packet to compute the total correlation after each addition. The assignment that causes the least increase in correlation is added to the final interleaving scheme.

Note that the interleaving scheme is fixed for a given data length, wavelet, and the number and capacity of packets, i.e., it is independent of the actual data that is to be transmitted. Thus, this interleaving algorithm can be run offline. Only the resulting pattern needs to be available at the transmitter to assign coefficients to packets with minimal computational overhead.

Example: Consider 15 coefficients resulting from a 4-level decomposition of a signal of length 16 that are to be distributed among 3 packets. Each packet can contain 5 coefficients. The assignment from algorithm computeInterleaving is shown in Figure 3. Since correlation drops across time and level, coefficients adjacent either in time or level get assigned to different packets.

```
Algorithm computeInterleaving ($C$, $N_1, \ldots, N_P$)
    returns $A(c) \in \{1, \ldots, P\}, \forall c \in C$
    $A(c_0) := 1$
    $A(c_i) :=$ UNASSIGNED, $2 \leq i \leq N$
    while there are unassigned coefficients in $A$
        minCorrelation := $\infty$
        for $i = 2 \ldots N$
            for $p = 1 \ldots P$
                if $A(c_i)$ = UNASSIGNED and
                number of coefficients in $p < N_p$
                    $A' := A$
                    $A'(c_i) := p$
                    if $r_{A'} <$ minCorrelation
                        minCorrelation = $r_{A'}$
                        $i^* := i$
                        $p^* := p$
                    end if
                end if
            end for
        end for
        $A(c_{i^*}) = p^*$
    end while
```

Fig. 2. Algorithm to compute an interleaving scheme that reduces in-packet correlation

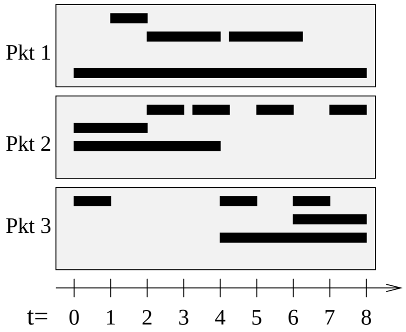


Fig. 3. Distributing 15 coefficients across 4 levels into 3 packets, each of capacity 5 coefficients using the computeInterleaving algorithm. Each coefficient is indicated by a filled rectangle. The position of each bar indicates the time/space support for that coefficient. The width indicates level: the wider rectangles correspond to coarser levels.

Algorithm computeInterleaving assigns the first P coefficients to P different packets. This bias in the initial assignment is removed by randomly selecting P coefficients and assigning them to different packets at the beginning of algorithm computeInterleaving.

B. Running time of the interleaving algorithm

The time taken to calculate the correlation between two coeffients is constant. If there are m coeffients in a packet p, the time taken to compute $r_A(p, c)$ for a single coeffient c under assignment A is $O(m)$ and to calculate $r_A(p)$ is $O(m^2)$. If a total of m coeffients are assigned among P packets, then the time taken to calculate r_A is

$$T(r_A) = O(Pm^2)$$

since there can be atmost m coefficients in any packet.

Let the total number of coefficients to be assigned be N. The `while` loop in algorithm computeInterleaving is run N times, since one coefficient is assigned at the end of every iteration. Let m be the number of assigned coefficients at the end of an iteration. The running time of an iteration is $P(N - m) \times T(r_A)$ since every combination of unassigned coefficient and packet is examined and the resulting r_A computed (lines 5-6 in Figure 2). The total running time of the algorithm is then

$$\sum_{m=1}^{N} P(N-m)T(r_A) = \sum_{m=1}^{N} P(N-m)O(Pm^2)$$

$$= O\left(P^2 \sum_{m=1}^{N} (N-m)m^2\right) = O(P^2N^4)$$

IV. INTERPOLATING MISSING COEFFICIENTS

A multi-level wavelet decomposition of a signal gives a set of detail coefficients at each level and a set of approximate coefficients at the highest level. These coefficients are transmitted between network nodes and are used to reconstruct the original signal at the receiver. Reconstruction of the signal proceeds from the bottom of the decomposition tree. The approximation coefficients at level n (A_n) are obtained from the approximation and detail coefficients at the higher level ($A_n = A_{n+1} + D_{n+1}$). The approximation coefficients at the lowest level correspond to the original signal. If some of these coefficients are lost during transmission, the reconstruction quality is affected.

The interleaving scheme described in Section III distributes coefficients among packets such that coefficients in a packet have correlated coefficients in other packets. These correlated coefficients can be used to replace coefficients that are lost due to packet drops in transmission. We now describe a coefficient interpolation scheme that uses both detail and approximate coefficients from a Haar wavelet decomposition to estimate missing detail coefficients.

Let A_l^t (D_l^t) denote an approximation (detail) coefficient at level l and time t. In the case of the Haar wavelet, the approximation and detail coefficients are related by the following equations:

$$A_l^t = \frac{A_{l+1}^{t/2} - D_{l+1}^{t/2}}{\sqrt{2}}, t \text{ is even}$$

$$A_l^t = \frac{A_{l+1}^{(t-1)/2} - D_{l+1}^{(t-1)/2}}{\sqrt{2}}, t \text{ is odd}$$

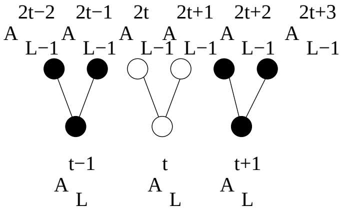


Fig. 4. Estimating missing detail coefficients from four neighboring coefficients. The filled circles indicate known coefficient values, the unfilled circled denote coefficients that are missing and have to be interpolated from the neighboring known values.

Let $x = D_l^t$ be a missing coefficient and let all coefficients at levels $> l$ be available either through correct transmission or interpolation at higher levels. (In this work, we assume that the approximation coefficients at the highest level are transmitted reliably. Since these coefficients are few in number, reliable transmission methods such as FEC may be used without incurring a large computation or transmission penalty. Thus, we discuss only estimation of detail coefficients.) Then, at level $l - 1$, it is not possible to reconstruct A_{l-1}^{2t} and A_{l-1}^{2t+1}. However, if neighboring coefficients D_l^{t-1} and D_l^{t+1} are available, then so are coefficients A_{l-1}^{2t-2}, A_{l-1}^{2t-1}, A_{l-1}^{2t+2}, and A_{l-1}^{2t+3} (Figure 4). We fit a third-degree polynomial between these four points and evaluate this fitted polynomial at times $2t$ and $2t + 1$. Let the fitted values at these times be P^{2t} and P^{2t+1} respectively. Then,

$$\frac{A_l^t + x}{\sqrt{2}} = P^{2t}$$

$$\frac{A_l^t - x}{\sqrt{2}} = P^{2t+1}$$

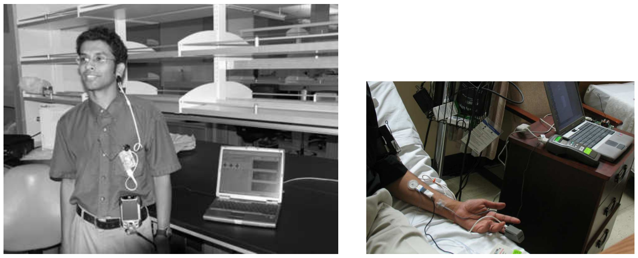
and we estimate the value of the missing coefficient D_l^t as

$$D_l^t = x = \frac{P^{2t} - P^{2t+1}}{\sqrt{2}}$$

Note that this interpolation scheme cannot be directly applied at the edges of a level. In such cases, the missing edge coefficient may be approximated by setting it to zero.

V. RESULTS

The data-sets used to evaluate the method were obtained from biosensors that would be interfaced with our wireless health monitoring system. Figure 5 shows how the sensors and the central handheld computer would be deployed on a subject. The sensors are a minimall invasive interstitial fluid alcohol sensor (ISF) [2], a pulse oximeter that measures heartrate (Pulse) and blood oxygenation (SPO2), and thermometers to measure skin (Tskin) and ambient (Tair) temperatures. Representative samples from these sensors are shown in Figure 6. Variations in ISF correspond to changing blood alcohol levels after consumption of an alcoholic beverage. Variations in Pulse and SPO2 correspond to intensity of physical exercise. The changes in Tskin and Tair are normal variations over the course of a day. Each signal sequence contains 128 samples though



(a) (b)

Fig. 5. (a) Subject wearing sensors. The handheld computer is attached at the waist. (b) Detail view of the ISF alcohol sensor attached to the forearm.

TABLE I

MEAN OF THE RECONSTRUCTION ERRORS AFTER LOSS OF A SINGLE WAVELET COEFFICIENT

Signal	L=2		L=3		L=4	
	PI	Z	PI	Z	PI	Z
ISF	**2.55e-3**	1.36e-2	**5.45e-5**	8.57e-4	**1.92e-5**	1.93e-4
Pulse	**7.77e-6**	4.93e-5	**2.81e-5**	3.57e-5	**1.97e-5**	2.05e-5
SPO2	**1.54e-7**	6.60e-7	**1.25e-7**	1.59e-7	**3.77e-8**	8.04e-8
Tskin	**3.35e-7**	1.27e-6	**2.63e-7**	6.94e-7	**6.20e-8**	1.51e-7
Tair	2.57e-7	**9.75e-8**	**7.40e-8**	2.88e-7	**8.11e-9**	3.84e-8
G-M	**1.84e-2**	2.78e-2	**6.74e-3**	1.15e-2	**2.20e-3**	4.34e-3

TABLE II

AVERAGE RECONSTRUCTION ERRORS AFTER A SINGLE PACKET LOSS

Signal	PI	Z	DCT
ISF	**1.11e-4**	1.13e-3	2.54e-4
Pulse	**7.70e-5**	1.01e-4	8.47e-5
SPO2	**2.74e-7**	4.12e-7	2.84e-7
Tskin	**4.39e-7**	1.06e-6	5.36e-7
Tair	**1.01e-7**	3.59e-7	1.07e-7
G-M	**1.88e-2** (1.10e-2)	2.66e-2 (1.42e-2)	2.24e-2 (1.22e-2)

the sampling interval is different for each modality (4 minutes for ISF, Pulse, and SPO2; 2 minutes for Tskin and Tair). We also generated Gauss-Markov ("G-M") sequences ($\alpha = 0.95$) and use these along with the physiological signals. Using synthetic datasets enables us to report average scores from multiple trials.

We measure the difference between two sequences, x_i and y_i, $i = 1 \dots N$ (the original signal and its reconstruction respectively), using the following error metric.

$$\frac{\sum_{i=1}^{N}(x_i - y_i)^2}{\sum_{i=1}^{N} x_i^2}$$

A. Reconstruction errors after single coefficient loss

We compare our interpolation scheme with replacing missing coefficients by zero. Since detail coefficients correspond to the high frequency portion of the data, setting these coefficients to zero is a reasonable approximation for most signals. This forms the basis for wavelet compression where detail coefficients of small magnitude are set to zero.

We perform a 7-level decomposition using the Haar wavelet on the data sequence. In our mote-based system, the wavelet transform was performed using an integer wavelet basis [17]. In this decomposition, there are 64 detail coefficients at the finest level ($l = 1$) and one detail coefficient at the coarsest level ($l = 7$). The coefficients at the coarsest levels encode the most information and are few in number. Thus these coefficients may be transmitted using a separate error correcting scheme without incurring a large overhead. In our discussion of interpolation results, we have assumed that the three coarsest levels are transmitted without error (7 coefficients). To test the interpolation scheme, we successively drop each coefficient at a level and approximate it using our interpolation scheme ("PI") and by replacing it by zero ("Z"). The signal is reconstructed with the approximated coefficient. The means of the errors with the original signal are reported in Table I. Our polynomial interpolation scheme outperforms the replace by zero scheme in most instances. Approximation by zero is appropriate when there is a sharp change in the signal value which cannot be predicted from neighboring sample points.

B. Reconstruction errors after packet loss

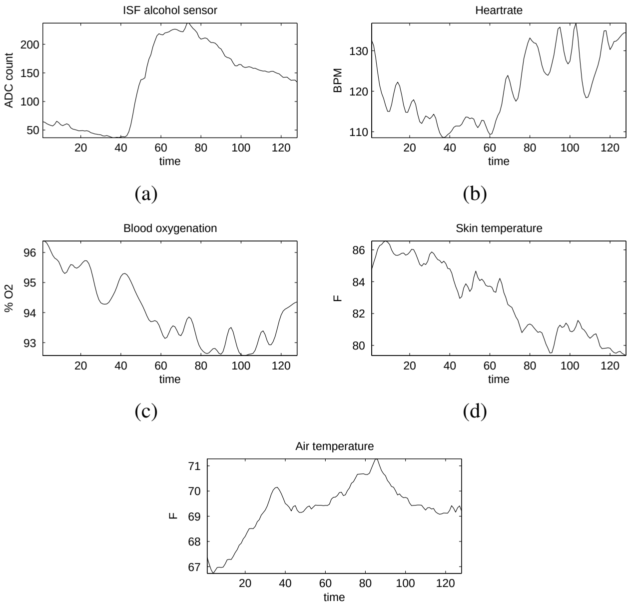
We consider the case where multiple coefficients are lost in a packet drop. We model each of the data sequences $y(n)$ as generated by a zero-mean Gauss-Markov process centered on a constant μ. The correlations between coefficients of a wavelet transform depend only on α. This value can be obtained from the autocorrelation of a Gauss-Markov process. μ is obtained from the mean of the data sequence. We obtained assignments of 120 wavelet coefficients to 10 packets (each with capacity 12 coefficients) from algorithm computeInterleaving.

We simulate transmission of each of the five datasets and calculate the average reconstruction error when one of the 10 packets is dropped during transmission. The (12) coefficients in the dropped packet are interpolated from adjacent coefficients or replaced by zero. We compare our interleaving scheme with that of first transforming the data into the DCT domain and then distributing consecutive DCT coefficients in different packets (as in [7]). The 8 lowest frequency DCT coefficients are assumed to be transmitted without loss as in our scheme. The results are reported in Table II. Note that the reconstruction error is the least when the wavelet interleaving is coupled with interpolation of missing coefficients. In particular, the interpolation step is responsible for a reduction in the reconstruction error. Thus, the correlations arising due to the varying spatial resolutions used in the wavelet transform, as compared to the DCT transform, are crucial to our approach.

Figure 7 is a pictorial representation of a typical interleaving pattern obtained from our interleaving scheme. 120 detail coefficients from a multi-level Haar wavelet decomposition is distributed among 6 packets. Note that coefficients that are close together in time or level are assigned to different packets.

VI. CONCLUSIONS

We presented a scheme for efficient transmission of data over noisy packet networks when power conservation is critical. The scheme consists of performing a wavelet decomposition of the signal, interleaving the resulting wavelet coefficients among the transmission packets, and approximating



(a) (b) (c) (d) (e)

Fig. 6. Data used for evaluation. a) ISF alcohol concentration, b) heartrate, c) blood oxygenation, d) skin temperature, and e) ambient temperature. Each time unit corresponds to 1 minute.

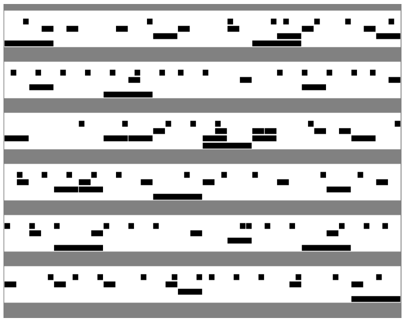


Fig. 7. Interleaving the 120 detail coefficients at levels 4-7 from a Haar wavelet decomposition of a signal of length 128.

missing coefficients at the receiver using an interpolation algorithm. The method is suitable for adaptive sensing since the level of decomposition can be varied. The quality of reconstruction was shown to outperform the replace-by-zero scheme at all levels for both real and simulated datasets. The interleaving and interpolation scheme also improved the reconstruction quality of these signals when their transmission suffered single packet drops.

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