Requirements for IoT Sensors Using Embedded Compressed Sensing Encoders with Deterministic Sensing Matrices

Felipe da Rocha Henriques, Lisandro Lovisolo and Eduardo Antônio Barros da Silva

***Abstract*— We consider a WSN monitoring environmental signals. Sensor nodes compress data employing the Compressive Sensing (CS) framework, exploring signals sparsity to reduce the number of transmissions. We propose the use of the Karhunen–Loève Transform (KLT) as sparsifying basis and design maximally incoherent deterministic sensing matrices. Real–life signals are used in simulation, and their CS measurements are quantized before transmission. The rate–distortion performance obtained after the reconstruction of monitored data is evaluated. Important requirements for using this framework in an IoT scenario are also investigated, such as the response time (latency) of the WSN, the impact of packet loss in the reconstruction of the sensed signals and the energy consumption of sensor nodes to transmit coded measurements. Simulation results show that the KLT–based deterministic sensing matrices overcome both Noiselets and DCT–based deterministic ones, and the proposed CS coding scheme is robust against packets loss.**

***Keywords*— IoT, WSN, Compressive Sensing, KLT, deterministic sensing matrix.**

I. Introduction

Currently, most individuals are connected to the Internet using several devices (smart-phones, tablets, smart-TVs, among others) employing the most diverse physical layer technologies ranging from wire-lined to wireless. The Internet of Things (IoT) [1] brings this connection to “things”, so that they can process data and share information, providing a framework for distributed applications. Some application domains and relevant scenarios for IoT are defined in [1]. One of them, that is the focus of this work, is *Environmental Monitoring*, which has been largely implemented using a Wireless Sensor Network (WSN) [2]. A WSN is an *ad hoc* network, in which sensor nodes are capable of communicating to deliver their measurements to a base station (sink node).

Such a scenario entails the basic IoT environment, that is composed by sensors, gateway and end–devices. The gateway may be used as a node to communicate directly with the sensors or it may also receive traffic from sensor nodes and offer it to the Internet. Furthermore, the data can be monitored from anywhere as in a home automation application [3], at the gateway or directly at the node.

For the WSN to scale at manageable costs, the sensors have memory and energy constraints. Thus, methods capable of increasing node autonomy are of relevance [4]. Following this, we consider the Compressive Sensing (CS) framework [5] as the data compression scheme in order to save sensor nodes energy [6]. CS explores the fact that signals have a sparse representation in a given basis and consequently can be represented using few non–zero coefficients. These are obtained through linear measurements that are incoherent with the sparsifying basis. As a result, sensor nodes just need to transmit few coefficients, saving energy and thence increasing autonomy. In [6], a circuit example shows that it is better to apply the CS coding framework in the digital domain (i.e., after the ADC – analog to digital converter) than in the analog domain (i.e., before the ADC). Linear programming or greedy algorithms are used at the sink node to reconstruct the monitored signal from the measurements [7].

Designing a good sensing matrix is a requirement for CS to work. Random methods provide statistically good matrices [8]; in contrast, in [9] the deterministic design of maximally incoherent sensing matrices for orthogonal or bi-orthogonal sparsifying bases is presented. Deterministic sensing matrices provide better rate–distortion performance than random sensing matrices [9]. In this work, we pursue this further to consider deterministic sensing matrices constructed using the Karhunen–Loève Transform (KLT) [10] as sparsifying basis. Doing so, we intend to increase the representation power of CS coefficients, thus providing a better rate–distortion performance.

The above is applied in a WSN-based IoT environment: **i**) sensor nodes measure physical variables such as temperature and humidity, **ii**) the CS scheme is used to compress data and produce/transmit **iii**) quantized CS coefficients. From these coefficients, **iv**) the sink reconstructs the original signal block by using a specific reconstruction algorithm. The analysis of such strategy allows to evaluate its use in an IoT scenario for environmental monitoring. We determine which are the sensors/network requirements for environment monitoring with using the CS–based encoder, regarding energy and rate–distortion performances.

Real–life environmental signals are considered in simulations [11] aimed at evaluating the performance of the deterministic optimal compressive sampling scheme. The analyzed parameters are the coding rate in function of distortion, the impact of signal coding in the response time/delay for data availability, the energy consumption in function of the coding rate and the packet loss.

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II. Compressive Sensing with Deterministic Sensing Matrices

A. Using Compressive Sensing for Signal Coding

Let a sensor node collect N samples of a signal $\mathbf{x} \in \mathbb{R}^N$. The CS framework considers this signal to have a sparse representation

$$\mathbf{s} = \mathbf{\Psi}\mathbf{x}, \tag{1}$$

where $\mathbf{\Psi} \in \mathbb{R}^{N\times N}$ is a transform matrix mapping $\mathbf{x}$ to a sparse $\mathbf{s}$. The sparsity assumption, which has been the basis for transform-based signal coding, means that most of the signal energy is concentrated in S few coordinates of $\mathbf{s}$. The CS framework pushes this concept further by coding the signal into M linear measurements (or coefficients) in the form of

$$\mathbf{y} = \mathbf{\Phi}\mathbf{x}, \tag{2}$$

in which $\mathbf{\Phi} \in \mathbb{R}^{M\times N}$ is called the *sensing matrix* with $S < M < N$. One observes that the m-th coefficient in $\mathbf{y}$ is obtained by the inner product between $\mathbf{x}$ and the measurement function $\boldsymbol{\phi_m}$ (the m-th row of *sensing matrix*). One can reconstruct an approximation of $\mathbf{x}$ from $\mathbf{y}$ looking for the sparsest $\hat{\mathbf{s}}$ such that

$$\mathbf{y} = \mathbf{\Phi}\mathbf{\Psi}^*\hat{\mathbf{s}}, \tag{3}$$

where $\mathbf{\Psi}^*$ is the complex conjugate transpose of $\mathbf{\Psi}$, and making $\mathbf{x} = \mathbf{\Psi}^*\hat{\mathbf{s}}$.

Sparsity is in general assumed the l_0 norm of the vector, the amount of non–zero entries of the vector. However, using such an approach to solve equation (3) leads to a combinatorial, NP–complete problem [5]. Alternatively, a common compromise is to minimize the l_1 norm instead [7], leading to

$$\hat{\mathbf{s}} = \arg\min_{\mathbf{s}} \|\mathbf{s}\|_1 \text{ s.t. } \mathbf{y} = \mathbf{\Phi}\mathbf{\Psi}^*\hat{\mathbf{s}}, \text{ producing } \hat{\mathbf{x}} = \mathbf{\Psi}^*\hat{\mathbf{s}}. \tag{4}$$

In the WSN monitoring application, CS can be used to reduce the energy consumed by sensor nodes for coefficients transmission since just M coefficients ($\mathbf{y}$) instead of N coefficients ($\mathbf{x}$) are required. The coefficients are easily obtained by simple multiplication of $\mathbf{x}$ by a matrix, with low energy consumption. Although traditional transform-based coding may potentially employ $S < M$ values when compared to the CS framework, any coefficient loss leads to a corresponding loss of signal energy. In contrast, the CS framework is more resilient, since the *sensing matrix* spreads the information/energy of a principal direction of $\mathbf{x}$ in a way that could be classified as being between the use of the N coefficients of $\mathbf{x}$ and the use of the S coefficients of $\mathbf{s}$ ($S < M < N$). Since one wants this to happen with a few coefficients as possible (small M), good sensing matrices design methods are required.

One should note that the values in $\mathbf{y}$ must be quantized for transmission to the sink node [4]. Upon reception, the sink node reconstructs the signal by solving the optimization problem in equation (4).

B. The LASSO Reconstruction Method

In this work, we employ the *Least Absolute Shrinkage and Selection Operator* (LASSO) [12] to reconstruct the monitored signal from received data. Concisely, the LASSO algorithm reconstructs the signal from the CS measurements imposing a thresholding operation on the coefficients and also on the l_1 norm maximum τ, i.e.

$$\arg\min_{\mathbf{x}} \ \|\mathbf{\Phi}\mathbf{x} - \mathbf{y}\|_2 \quad \text{s.t.} \quad \|\mathbf{x}\|_1 \leq \tau. \tag{5}$$

We use the LASSO implementation contained in the SPGL1 software packet [13].

C. KLT–Based Sensing Matrices

In the CS framework, in principle, the more incoherent that $\mathbf{\Phi}$ is to the sparsifying basis $\mathbf{\Psi}$, the less coefficients has the $\mathbf{y}$ guaranteeing provably good signal estimates [5]. It has been shown in [9] that, given an orthogonal $\mathbf{\Psi}$ ($N \times N$) the maximally incoherent sensing matrix $\mathbf{\Phi}$ ($M \times N$) to it is given by

$$\mathbf{\Phi} = \boldsymbol{H}\mathbf{\Psi}, \tag{6}$$

where $\boldsymbol{H}$ is formed by rows of the Hadamard matrix.

In this work, we explore the design given by eq. (6) and evaluate the use of maximally incoherent deterministic sensing matrices to the KLT in the CS framework. The KLT obtains uncorrelated components providing the best coefficients energy concentration [14]. Nevertheless, for designing the KLT it is necessary to have samples of the class of signals to process. Although in the past this has been appointed as a technical difficulty for designing generic compression systems, for compressive sensing some signal space/characteristics knowledge is always assumed to improve CS performance [15].

III. Results of Requirements for IoT Sensors

We start this section evaluating the possible gain of using the KLT for sensing matrix design. For simulation of the IoT scenario, we consider the Intel Berkeley laboratory WSN data [11] – sensor nodes collecting environmental signals for more than a month, from which we extract temperature and humidity signals.

We compare the results of $\mathbf{\Psi}$ being the KLT or the DCT [16] basis. The KLT basis is assumed to be known at both coder and decoder. It is obtained from realizations of the monitored signals, which in turn are not used in the RD assessment.

A. Rate–Distortion Performance Evaluation

Quantization is considered in the presented rate–distortion performance analysis. For that purpose distinct bit-depth quantizers are used testing the performance at different rates. The rate at which each sensor transmits quantized CS coefficients is defined as

$$R = \frac{M}{N} \times H(y_Q), \text{bits/coeff}, \tag{7}$$

in which N is the signal block dimension of the collected data, M is the number of coefficients transmitted by sensor nodes and $H(y_Q)$ is the entropy (in bits per sample) of the quantized measured data [1].

[1]For entropy computation, we consider that each possible quantizer output value occurs at least once. Doing so, unused reconstruction values are adequately taken into account. In addition, the experiments use different estimates of $H(y_Q)$ depending on M and quantizer bit-depth B. However, if an adaptive arithmetic encoder was considered, the rate would be approximated by the entropy.

As leading signal reconstruction metric (the one used for algorithm evaluation) we employ the *Normalized Mean Squared Error* (NMSE)

$$\text{NMSE} = \frac{E[(x-\hat{x})^2]}{\| x \|^2}, \tag{8}$$

where $E[\cdot]$ is the expected value operator, x is the actual data value and $\hat{x}$ its reconstructed version.

For each rate R, the NMSE is computed and, to yield a more accurate rate-distortion (RD) analysis, each point in the presented RD curves results from an ensemble of 100 runs, each one with a distinct block of samples, and the NMSE is presented in dB scale.

B. CS–Based Encoder Performance

Figure 1 presents the RD compromise for coding the temperature signal using a deterministic sensing matrix or a one based on Noiselets [8]. These CS-encoder designs are denoted by DCT + Deterministic and DCT + Noiselets, respectively. The same sparsifying basis is assumed in the two cases. However, in the deterministic approach, one constructs the sensing matrix using equation (6), while in the second this is done using Noiselets [8]. For the results in Figure 1, $N = 512$ samples, the quantizers have varying bit-depths B= 4, 6 and 8, and $M \in \{16, 32, 64, 128, 256, 300\}$. As one readily sees, the deterministic sensing matrix brings improvements in rate-distortion performance over the one using Noiselets.

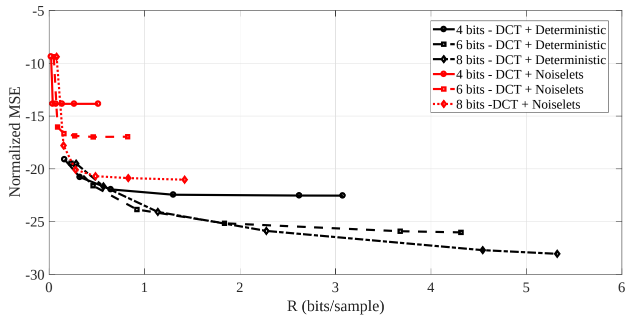

Fig. 1. RD performance for the reconstruction of temperature for the deterministic (DCT + Deterministic) and random (DCT + Noiselets) sensing matrices (DCT is the sparsifying basis). The signal block has $N = 512$ samples, the quantizers have bit–depths B= 4, 6 and 8, and $M \in \{16, 32, 64, 128, 256, 300\}$.

We now test the proposal of using the KLT as sparse basis in the CS scenario. The resulting RD performance is compared against the one obtained for deterministic sensing matrix (computed for the DCT basis) in Figures 2 and 3; these present the RD performances of the CS quantized encoder for temperature and humidity signals, respectively. One notes a gain in using the KLT in place of the DCT. The length of signal block, quantizer bit–depths and amount of CS coefficients are the same as those used in the previous experiment.

One observes that for both monitored signals an improvement in the reconstruction of the signals (with a decrease in the NMSE) as rate increases, since more coefficients (M) are used in the reconstruction procedure. An improvement in the reconstruction can also be observed when sensor node uses quantizers with more bits. Moreover, we verify a better rate–distortion performance for results considering KLT as the sparsifying basis, since this transform is the one that makes the signals the most sparse, and the deterministic sensing matrix used is optimum for the given basis.

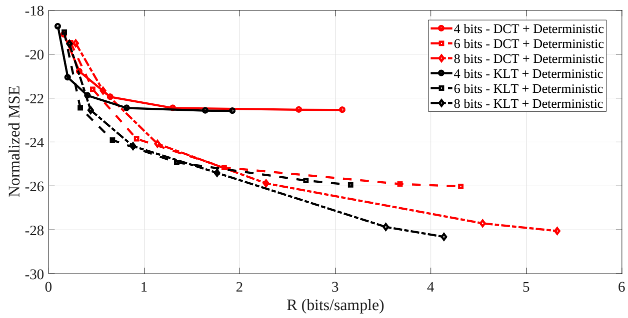

Fig. 2. RD performance for the reconstruction of temperature for KLT–based (KLT + Deterministic) and DCT–based (DCT + Deterministic) deterministic sensing matrices. The signal block has $N = 512$ samples, the quantizers have bit–depths B= 4, 6 and 8, and $M \in \{16, 32, 64, 128, 256, 300\}$.

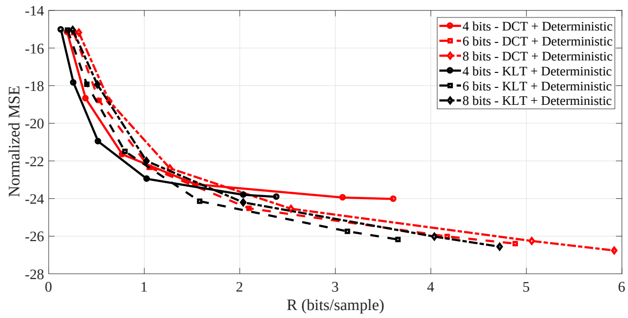

Fig. 3. RD performance for the reconstruction of humidity for KLT–based (KLT + Deterministic) and DCT–based (DCT + Deterministic) deterministic sensing matrices. The signal block has $N = 512$ samples, the quantizers have bit–depths B= 4, 6 and 8, and $M \in \{16, 32, 64, 128, 256, 300\}$.

C. Resilience to Packet Loss

We now evaluate the impact of packet loss in the RD performance. The wireless channel is prone to packet loss [17], and the CS encoder deals with it as described in the sequel. While sensor nodes transmit M quantized CS coefficients, the sink node may receive only $L \leq M < N$ coefficients. One supposes the existence of sequence numbers in the packets, a common practice in several network standards since it allows to identify lost frames in the link layer or to reorder segments in the transport layer. These sequence numbers may be used in the CS reconstruction to identify the lost measurements and thus ignore them in the reconstruction procedure – i.e., coefficient losses is simply modeled as using a sensing matrix with pruned rows corresponding to the missing coefficients.

Now, we empirically evaluate the RD performance of the CS scheme using the KLT-based deterministic sensing matrix under several packet loss conditions, and compare it against the former one using DCT as the sparsifying basis under the same packet loss conditions. We present results for packet loss percentages of 0%, 10%, 30% and 50%. A 0% packet loss means that all packets were received and a 10% packet loss means that in average one in ten packets is lost. All combinations of packet loss rate, bit-depth (B) and number of coefficients (M) have been simulated. The dimension of the signal block is set to $N = 512$; sensor node transmits $M \in \{16, 32, 64, 128, 256, 300\}$ CS coefficients; and bit–depths are set to $B \in \{4, 6, 8, 10\}$.

Figure 4 shows the RD convex hulls for the reconstruction of the signal using the KLT as the sparsifying basis. The convex hulls are the operational curves of sensor nodes, i.e., the quantizers that produce the best RD performances. We can observe just a small decrease in the NMSE in the reconstruction when data is lost, showing that the proposed CS scheme is robust against packet loss. Figure 5 compares the KLT with the DCT as the sparsifying basis for 0%, 10%, 30% and 50% packet loss. From these results one observes that the gain in using the proposed sensing matrices is not jeopardized by losing packets.

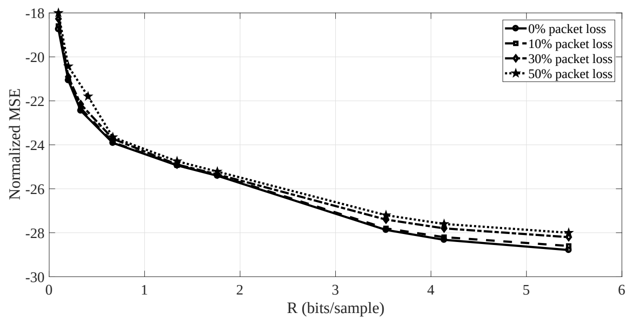

Fig. 4. RD convex hulls for the reconstruction of temperature ($N = 512$ samples) under different packet loss percentages using the KLT as the sparsifying basis and deterministic sensing matrices.

D. WSN Response Time and Energy Consumption

The CS-based coding strategy needs the sensor node to first store N samples of the interest signal, then to project the signal on the sensing matrix to generate the M CS coefficients. These are then quantized and forwarded to the sink node. This imposes a time interval/delay for data to be available at the sink. We will refer to this delay as the WSN Response Time.

We have seen that as the quantizer bit-depth and M increase, the signal quality also increases at the expense of an increase in rate. In this section, we empirically evaluate other possible compromises of the CS-encoder parameters (N, M and B) and aspects such as energy consumption and response time. We consider the reconstruction of a temperature signal, quantizer bit–depths $B \in \{4, 6, 8, 10\}$ and signal block lengths $N \in \{128, 256, 512, 1024\}$ collected samples; for $N = 128$ samples, sensor nodes transmit $M \in \{16, 32, 64, 80, 100\}$ coefficients, for $N = 256$ samples, $M \in \{16, 32, 64, 128, 200\}$, for $N = 512$ samples, $M \in \{16, 32, 64, 128, 256, 300\}$, and for $N = 1024$ samples, $M \in \{16, 32, 64, 128, 256, 512\}$. KLT is considered as being the sparsifying basis $\mathbf{\Psi}$.

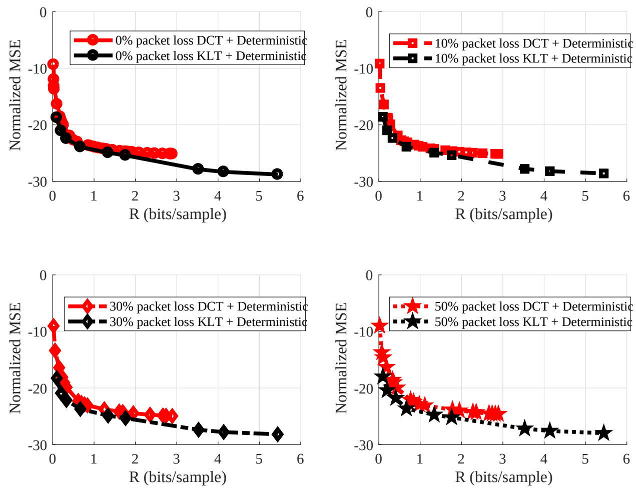

Fig. 5. RD convex hulls for the reconstruction of temperature ($N = 512$ samples) under different packet loss percentages for both the KLT and the DCT as sparsifying bases.

Figure 6 presents the RD convex hulls for the recovered temperature signal (these are obtained as in the previous sections) using distinct lengths N for the signal block. As one observes, RD performance improves as N increases. This is expected since CS explores sparsity better as N increases. Nevertheless, N cannot be to large, for augmenting the signal block produces a higher response time, since more time is required to collect the N samples.

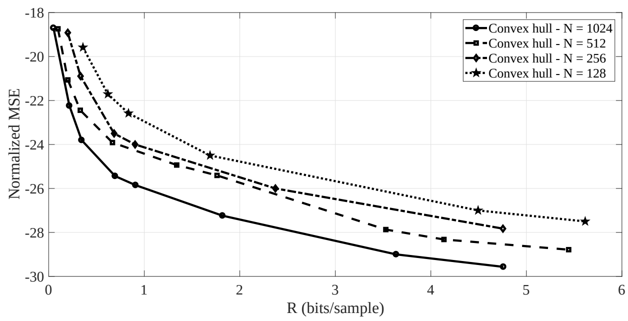

Fig. 6. Rate–distortion convex hulls for the reconstruction of temperature signal with LASSO varying the length of monitored signal block (N), using KLT as the sparse basis.

In order to better investigate the IoT requirements based on the length of signal block, we propose the following experiment. We consider that a fifteen-node WSN is monitoring a temperature signal. These are a subset of the 54-sensors from the Intel Berkeley Research lab [11]. A single sensor node S_{47}, located at $(39.5, 14)$ m [2], collects temperature samples and transmits the measurements to the sink node (S_0), located at $(0.5, 17)$ m. The other thirteen nodes are used as routers to forward the packets from sensor to sink. In each of the 10 simulation runs used to average the results, the position of the

[2]The coordinates are relative to the upper right corner of the lab.

thirteen routers is drawn from the remaining ones. TrueTime 1.5 [18] is used to perform the simulations, the IEEE 802.15.4 standard [19], referred to as ZigBee and widely used for WSN and IoT, is considered for communication between nodes while the AODV (*Ad hoc On–Demand Distance Vector*) routing protocol is used for routing. To evaluate energy consumption, we consider a state–based energy model [4] for the sensor nodes. The active state cycled among the operation modes: measurement, processing, transmission and data reception. These operation modes have different power consumptions, which multiplied by the time spent in the activity provide an estimate of the consumed energy.

Table I presents the response time of the WSN and the energy consumption (per sample) of the transmitted sensor node for distinct values of N. Aiming at a fair comparison, a fixed reconstruction quality is imposed, and one selects an NMSE around -24 dB. For each N the corresponding M and quantizer for that NMSE are employed, yielding: $M = 32$ coefficients and $B = 8$ bits for $N = 128$; $M = 32$ coefficients and $B = 8$ bits for $N = 256$; $M = 32$ coefficients and $B = 6$ bits for $N = 512$; and $M = 32$ coefficients and $B = 6$ bits for $N = 1024$. As expected, the response time increases with the signal block length. For emergency situations, this is an issue to be considered if fire alarm is one of the WNS objectives, since the larger the block length N, the slower the network response, i.e., the larger the response time.

On the other hand, one observes from the numbers in Table I that energy consumption reduces as N increases. This is so because the CS-encoder better explores signal sparsity as N increases, being required to transmit a smaller ratio of measurements relative to the block length, i.e., M/N decreases as N increases, consuming less energy per coded signal sample or observation time interval.

TABLE I

RESPONSE TIME AND ENERGY CONSUMPTION (PER SAMPLE) FOR DIFFERENT VALUES OF N AND A FIXED NMSE OF -24 DB.

N	Resp. Time (sec)	Energy Cons. (J/sample)
128	15.8	0.0017
256	28.6	0.0013
512	54.2	0.0011
1024	105.4	0.0009

IV. CONCLUSIONS

In this work, we employed a WSN monitoring environmental signals in an IoT environment. Sensor nodes use Compressive Sensing as a data compression framework. Doing so, one intends to provide a transmission scheme with low complexity, since sensor nodes have memory and energy constraints.

We proposed the usage of KLT as the sparsifying basis within the design of maximally incoherent sensing matrices, aiming at providing sensing functions which concentrate more energy into the CS coefficients and, then improving rate–distortion performance.

We verified that the KLT–based deterministic sensing matrices overcame both the Noiselets and the DCT–based deterministic ones in terms of rate–distortion performance. We evaluated the response time of the WSN, varying the length of the signal block, and we also analyzed the impact of packet loss in the reconstruction of the environmental signal.

We concluded that sensors using embedded CS encoders are suitable for WSN–based IoT environments, and the usage of KLT as the sparsifying basis $\boldsymbol{\Psi}$ improves the encoder performance with respect to the rate–distortion behavior.

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