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AdaptCast: An Integrated Source to Transmission Scheme for Wireless Sensor Networks

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Abstract—This paper introduces AdaptCast, an integrated source to transmission scheme for wireless sensor networks (WSNs) that efficiently represents collected data and increases their robustness against channel errors across a wide range of signal to noise (SNR) values in a rateless fashion. AdaptCast leverages sparsity inherent in the majority of physical signals in order to parsimoniously represent them without relying on a specific signal model. The proposed scheme does not suffer from the sudden degradation in the tradeoff between distortion and SNR of rated channel coding schemes due to its direct, relative bit importance preserving modulation mapping. In addition, it does not require continuous feedback or channel state information (CSI) as a result of its rateless operation. Apart from point-to-point transmission, AdaptCast enables efficient multicasting to a set of nodes, serving each of them at a rate commensurate to its individual channel quality. We demonstrate AdaptCast’s application-independent operation by using several typical signals captured in WSNs. Based on our analysis and simulation results, considering the tradeoff between distortion and channel quality, AdaptCast performs close in a point-to-point scenario to an idealized layered transmission scheme with instantaneous CSI and offers significant benefits in multiuser settings.

I. INTRODUCTION AND BACKGROUND

Wireless sensor networks (WSNs) have a rapidly increasing range of target applications, such as environmental monitoring, warehouse inventory tracking and continuous health monitoring. Although different WSNs exhibit diverse application requirements, a majority of them captures compressible analog signals, quantizes them to a certain precision and aims to transmit them to one or more nodes with little distortion while maintaining low power consumption. A vast literature exists on design approaches and theoretical guarantees for acquiring, representing and coding analog signals in WSNs; in the following presentation only a small subset of representative works are considered and compared.

A common modular approach, justified by Nyquist’s sampling [1] and Shannon’s separation theorem [2], is to decouple signal acquisition, compression of sources (source coding) and reliable transmission (channel coding), as shown in Fig. 1(a). Source coding techniques compress acquired data by transforming them to other domains and/or exploiting statistical source properties [3], [4]. Channel coding techniques insert redundancy in transmitted data for increased communications reliability in the presence of channel noise [5].

Although most practical channel coding schemes operate without knowledge of the source treating equally every bit, unequal error protection schemes have been proposed weighting the assignment of additional resources, i.e. power, frequency or rate redundancy, to each bit depending on its relative importance [6], [7], [8]. Thus, an error is less likely to occur in the most significant bit (MSB) of a r-bit transmitted signal value, resulting in lower complexity or better performance in certain scenarios. Similarly to the concept of unequal error protection, schemes have also been proposed for “approximate” communications [9], [10]. Their goal is to extend the range of channel SNR values for which transmission can be achieved, allowing for information delivery within some distortion limits rather than asymptotic perfect reconstruction, which is the goal of most modern communication systems.

Rapid fluctuations in the quality of the wireless medium caused by such factors as mobility and external interference, deteriorate performance of rated channel coding schemes resulting in poor connectivity or even communication outages. This behavior is usually called threshold effect. Channel estimation and rate adaptation techniques partially address the problem by adjusting transmission parameters depending on the experienced channel but they are limited by the fundamental trade-off of measuring channel quality versus transmitting more signal energy [11], [12]. Rateless coding schemes have been proposed as an alternative approach without requiring feedback information [13], [14], [15] and some cross-layer schemes have been proposed to provide a wider range of operation in terms of channel SNR values [16], [17], [18].

Joint source-channel coding schemes, as shown in Fig. 1(b),
simultaneously compress and enhance reliability of transmitted information. Although these schemes might guarantee gracefully degrading quality of received information and lower complexity than the layered approach, there are usually signal-specific and ad-hoc approaches [19]. In addition, they might imply implementation unfriendly, fully analog or hybrid systems [20].

More recently, compressed sensing (CS) has been proposed as an alternative for efficient representation of sparse signals to source coding based on incoherence and underdetermined signal reconstruction [21], [22]. Systems with CS acquisition, followed by typical channel codes, as the one shown in Fig. 1(c), do not assume knowledge of the underline signal model but require channel state information (CSI) for appropriate rate selection and do not perform well in multiuser scenarios.

In summary, the most prominent drawbacks and challenges associated with the prevailing acquisition, source and channel coding techniques in WSNs are the following:

- Signal-specific assumptions preventing use across multiple applications
- Threshold effect of channel coding schemes
- Poor performance in multiuser scenarios
- Requiring instantaneous feedback and CSI

In this paper, we present AdaptCast, an integrated source representation to transmission scheme which addresses all the aforementioned challenges and its block diagram is shown in Fig. 1(d). AdaptCast uses concepts from CS in order to take advantage of the inherent sparsity in physical signals and efficiently represent the captured information without requiring a detailed signal model. In addition, AdaptCast does not suffer from the threshold effect of standard channel coding schemes, providing graceful tradeoff between distortion and SNR owing to its distance preserving modulation mappings. Unlike standard mappings minimizing bit error rate (BER), such as Gray coding, AdaptCast’s integrated approach directly maps amplitude information to modulated symbols in the constellation diagram minimizing distortion. In particular, this results in inherent unequal error protection for additive channel noise which locally perturbs transmitted symbols, affecting only their LSBs. Furthermore, AdaptCast efficiently enables broadcasting, simultaneously serving multiple users at the highest possible information rate that can be served at. Finally, it operates in a rateless fashion without requiring channel estimation and continuous feedback for rate selection.

We evaluate AdaptCast’s signal independent operation by using several signals typically encountered in WSNs. In addition, we compare AdaptCast’s direct modulation mapping against a BER-based one, emphasizing the benefits of the relative distance preservation in the mapping process. We also demonstrate the graceful tradeoff between distortion and channel quality by using an electrocardiography (ECG) signal. Finally, considering the distortion and SNR tradeoff, we compare AdaptCast’s performance against an idealized transmission scheme with instantaneous and perfect CSI. The idealized scheme consists of a lossy transform-based compression algorithm and a physical (PHY) layer of adaptive rate through different modulation schemes and forward error correction (FEC) rates. Our results show that AdaptCast can efficiently transmit information in WSNs across a wide range of channel conditions, performing close to the idealized scheme in a unicast scenario, providing significant advantages in a broadcasting setting.

The rest of the paper is structured as follows. Section II describes AdaptCast’s transmission design while Section III presents the reception and reconstruction approach. Section IV presents the simulation setup and the performance evaluation of the proposed scheme. Finally, Section V provides a discussion on some practical challenges associated with implementing AdaptCast and concludes the paper.

II. TRANSMITTING WITH ADAPTCAST

AdaptCast uses a linear transformation based on random projections to efficiently represent sparse captured signals. Encoded coefficients are mapped to a dense constellation with order matching their precision and transmitted through the wireless medium. The matching between the constellation order and coefficients precision preserves the relative importance of data bits and provides inherent unequal error protection.

A. Signal Acquisition in AdaptCast

AdaptCast follows the random projections and incoherent bases principles to provide a parsimonious signal representation, similarly to CS. Thus, all theoretical guarantees on achievability and performance bounds hold for AdaptCast’s representation transformation and signal reconstruction. In more detail, assume a $N$-dimensional signal $x$ ($x \in \mathbb{R}^N$) needs to be transmitted to an intended receiver and let $\Phi \in \mathbb{R}^{M \times N}$ be a measurement matrix. According to [21], if $x$ is $k$-sparse in a domain represented by the matrix $\Psi \in \mathbb{R}^{N \times N}$, i.e. $x$ can be written as $x = \Psi \cdot r$ where $r$ has $k$ non-zero coefficients, and the measurement matrix satisfies some conditions [23], then only $M = O(k \log N)$ elements, given by $y = \Phi \cdot x$, suffice to reconstruct the initial signal with very high probability. Each element of $y$ is called measurement of $x$. Thus, by only communicating $M$ measurements of $x$ the receiver can decode the initial signal within some desired distortion limits.

The recovery of the reconstructed signal $\hat{x}$ from the incomplete set of measurements is usually done through an optimization problem which can be formulated as:

$$\min_{\hat{x} \in \mathbb{R}^n} \| \hat{r} \|_1, \text{ subject to } y = \Phi \cdot \Psi \cdot \hat{r},$$  \hspace{1cm} (1)

where $\hat{x} = \Psi \cdot \hat{r}$. In the presence of acquisition or channel noise, the above optimization problem can be slightly modified to a noise-aware reconstruction algorithm by relaxing the equality constraints [24]. As the number of measurements ($M$) varies, distortion and amount of data to be transmitted changes. In the rest of the paper, we call the ratio $M/N$ as compression ratio and we measure the achieved distortion by the percentage...
Signal measurements

![Fig. 2. AdaptCast’s representation performance for four different signals encountered in typical WSN applications: ECG signal [25], IR image from thermal camera [26], seismic signal [27] and sound (hydraulic pressure) signal from underwater leak detection [28].](image)

![Fig. 3. AdaptCast uses dense modulation schemes in which signal measurements (y_i) are mapped to modulated symbols (s_i) for transmission through a direct mapping.](image)

The root-mean-square difference (PRD):

\[
PRD = \frac{\| x - \hat{x} \|_2}{\| x \|_2} = \sqrt{\frac{\sum_{i=1}^{N} (x_i - \hat{x}_i)^2}{\sum_{i=1}^{N} (x_i)^2}} \leq 100\%.
\] (2)

The choice of this particular metric is mainly because it normalizes the error energy by the initial signal energy, unlike other metrics such as mean square error (MSE), and it is better suited to comparison of different signal models and settings.

Although random projections and CS form an information theoretic suboptimal compression method in terms of bit rate [29], it has been widely considered as a candidate method for signal-independent acquisition in resource constrained systems mainly because of its low computational implementation requirements and the fact that many typically encountered in WSNs signals naturally exhibit high sparsity levels [30], [31]. The achieved end-to-end distortion of AdaptCast’s representation process depends on the signal sparsity and the desired compression ratio; however, it is signal agnostic without requiring or being tailored to a detailed signal model. As an example, representation performance is shown in Fig. 2 for an ECG signal from MIT-BIH arrhythmia database [25], images from a thermal camera [26], seismic data [27] and a hydraulic pressure signal from underwater pipe leak detection systems [28]. As the compression ratio increases, signal is represented with less coefficients, resulting in higher distortion levels.

As it is shown and thoroughly explained in Section III, AdaptCast’s acquisition process not only results in a parsimonious signal representation but also in increased data reliability by enabling the reconstruction algorithm to leverage the signal structure and suppress the added channel noise.

**B. Signal Transmission in AdaptCast**

After the signal has been efficiently represented and the measurements have been quantized, a dense constellation of most typical digital modulation schemes, i.e. QAM and FSK, can be used to transmit the information across the channel. Standard PHY randomization techniques, such as scrambling and interleaving, and FEC schemes usually result in obliviously created modulated symbols. However, AdaptCast does not use any of these techniques ensuring that measurements’ relative information is preserved across their entire transmission. In particular, the proposed design preserves the relative importance of transmitted bits by using a direct, distance-based mapping rule.

An example of such a transmission approach is shown in Fig. 3. A QAM modulation scheme is used with a constellation order that enables direct mapping of quantized measurements y_i’s to constellation symbols s_i’s. This property guarantees that additive channel noise will only locally perturb the transmitted data values depending on the experienced channel quality, similarly to analog modulation schemes. For instance, if the ‘011’ symbol is transmitted on the Q-axis and noise causes its demodulation as a neighboring symbol, e.g. ‘100’, the absolute value of the error is minimum although three error bits, defined by the conventional BER analysis approach, have occurred. Thus, unlike Gray coding that ensures one bit error between neighboring symbols in the constellation diagram, AdaptCast’s direct mapping maintains relative bit significance and provides inherent unequal error protection.

**III. RECEIVING WITH ADAPTCAST**

At the receiver, AdaptCast demodulates the received symbols and reconstructs the initial signal corrupted by the channel noise. Firstly, a standard digital demodulation stage is used, having the same characteristics (i.e. constellation order and mapping), with the transmitter. AdaptCast’s transmission paradigm emphasizes that BER is not always the most efficient metric to quantify and optimize performance of communication systems and applications aiming to transmit information within some distortion limits. This is shown in Fig. 4 in which the distortion of a randomly generated and quantized in five bits signal is transmitted through an AWGN channel. Gray coding is used for all constellation orders corresponding to dashed lines while the solid one corresponds to AdaptCast’s direct mapping. The performance difference between the two mapping approaches is mainly captured in the slope.
Fig. 4. Effect of the constellation order and mapping approach on the received signal distortion. Gray coding is used for all constellations with dashed lines while direct mapping is used for the constellation corresponding to the solid one.

Fig. 5. Magnitude of error in the received 5-bit samples transmitted over the channel.

Fig. 6. Normalized distribution of errors in each bit position. Bit 1 corresponds to MSB and bit 5 to LSB.

Writing PRD as

\[ PRD = \frac{\sum_{i=1}^{N} (\sum_{j=1}^{k} b_{ij} 2^{j-1} - \sum_{j=1}^{k} \hat{b}_{ij} 2^{j-1})^2}{\sum_{i=1}^{N} (\sum_{j=1}^{k} b_{ij} 2^{j-1})^2} \times 100\%, \]

and calculating its expected value for different SNR values, we get similar curves as in Fig. 4. In the case of AdaptCast, \( P(|b_j - \hat{b}_j|) \) reduces exponentially for the considered AWGN channel as bit positions of higher importance are considered, following the noise distribution.

AdaptCast uses a dense constellation with symbols having small distances from their neighboring ones, and so channel noise affects mainly their LSBs. Numerous signal denoising methods have been proposed in the literature, successfully suppressing unwanted noise in captured or received signals. The vast majority of them is application specific [33], [34], making use of precise signal features to identify and separate noise. However, since AdaptCast targets a wide range of WSNs applications, a signal-agnostic method is used based on sparse signal recovery principles. Basis Pursuit (BP) [21], Orthogonal Matching Pursuit (OMP) [35], ROMP [36] and CoSaMP [37] are some widely used reconstruction methods, each of them with different reconstruction quality and computational complexity. AdaptCast uses an OMP-based algorithm, mainly because of its robustness in the presence of noise and relatively low computational requirements. Fig. 7 shows the reconstruction distortion of the algorithm for an ECG signal [25] transmitted through an AWGN channel, parameterized by the number of measurements (\( M \)), or equivalently, the compression ratio. It can be seen that the reconstruction algorithm used performs well across a wide range of SNR values and efficiently increases robustness of transmitted data.
IV. SIMULATIONS AND PERFORMANCE EVALUATION

We evaluate AdaptCast’s performance in the context of a health monitoring application in which we assume that a captured biosignal is transmitted from a sensor node to a receiving hub. In addition, we comment on its advantages in a multiuser scenario. In more detail, we use an ECG signal from [25], which is sampled at 360Hz and quantized in 8 bits, without any preprocessing or filtering. Blocks of 2048 samples are used and performance is measured in terms of the achieved distortion in the reconstructed signal.

A. Compared Approaches

We compare AdaptCast against an idealized layered scheme following Shannon’s separation theorem. Although practical source and channel coding schemes are considered, we provide a marked advantage to it by assuming the existence of a genie assisting the rate adaptation process. In the rest of the paper, we refer to it as idealized separation scheme. This scheme uses a state-of-the-art lossy ECG compression scheme which includes a wavelet transformation with adaptive coefficients thresholding, similar to [38]. A BCH code supporting two coding rates of (63,30) and (63,51) is used as the channel coding method, a typical choice in numerous protocols for WSNs, such as ZigBee and Bluetooth. In addition, in the PHY of the idealized scheme a QAM modulation scheme of three constellation orders (QAM-22, QAM-24 and QAM-26) is used. In order to more efficiently transmit the collected information depending on the experienced channel SNR, this scheme adapts its rate among the two channel code rates and the three modulation orders. We assume the rate selection of the idealized scheme is performed by the genie having perfect and instantaneous CSI at the transmitter, always making the optimal rate selection. Considering any practical rate adaptation method or delayed/imperfect CSI would incur a considerable performance degradation.

AdaptCast’s system parameters are optimized once for the specific application, providing the best balance between compression performance, resilience against channel noise and reconstruction distortion, and are fixed during the entire experiment. In more detail, the number of measurements \( M \) is 800 and a QAM-212 modulation scheme is used. Unlike the idealized scheme, AdaptCast does not use a signal-specific source coding scheme tailored to a unique application. In addition, no CSI is required at the transmitter since it operates in a rateless fashion. Although the reduced feedback information is a crucial design property of AdaptCast that can lead to significant performance gains, it is not quantified in the comparison results of this work since we want to decouple any advantage associated with improved feedback mechanisms from benefits related to the proposed novel transmission method.

B. Performance Comparison

The performance of the two schemes in a point-to-point scenario is plotted in Fig. 8. As explained earlier, the idealized scheme has six different rate configurations corresponding to the dashed lines. All rate configurations exhibit similar behavior, performing well above a SNR value and having a rapid performance degradation below this value. As expected, lower coding rates and smaller constellations correspond to smaller threshold SNR values. Assuming the existence of the genie selecting the highest possible transmission rate which results in the lowest distortion, the performance of the idealized scheme is the lower envelop of all coding rates. For instance, at SNR of 20dB the idealized scheme uses QAM-26 and BCH (63,30) since choice of higher coding rate would result in excessive distortion and lower rate would lead to unnecessary use of resource, e.g. power and bandwidth. It becomes clear that the CSI advantage of the idealized scheme means that the deleterious effect of rapid SNR changes, affecting any rate separation-based scheme, does not cause performance degradation.

AdaptCast’s performance is represented by the solid line in Fig. 8. Without making use of CSI and being signal model independent, AdaptCast performs close to the idealized scheme. In the high SNR regime, the additional distortion is due to the sparse representation and reconstruction algorithm. As the SNR decreases, AdaptCast’s distortion is smoothly increasing resulting in a graceful tradeoff between reconstruction quality and channel noise. This is achieved by the preservation of the relative bit importance and the direct mapping of signal amplitude information to modulated symbols.

In addition to good performance in point-to-point scenarios, AdaptCast can offer significant advantages in multiuser settings in WSNs. For instance, considering a broadcasting scenario, a sensor node using the predominant layered schemes for WSNs would transmit in the lowest rate corresponding to the receiver with the worst channel and collecting feedback information from all intended receivers could significantly limit the overall performance. However, because of its analog-like modulation and rateless coding method, AdaptCast can achieve information transmission to each node with distortion commensurate with its channel quality and without requiring feedback information.
V. DISCUSSION AND CONCLUSION

In this paper, we present an application-independent integrated source representation to transmission scheme, called AdaptCast, for efficient communication of captured sparse signals in WSNs. AdaptCast leverages sparsity existing in many physical signals to parsimoniously represent them and, by preserving their relative bit importance during transmission, it achieves graceful tradeoff between distortion and channel SNR. According to our simulations results, it performs close to an idealized layered scheme with perfect CSI in a point-to-point scenario and provides several performance benefits in multiuser settings.

AdaptCast does not introduce any computational intense algorithm in the transmitting sensor nodes, limiting its encoding process to a linear operation and pushing most of the system’s complexity to the receiver’s side. The required dense constellations impose relatively strict specifications on the RF components, such as linearity and phase noise requirements, however several works, including [10], [15] and [39], have demonstrated the feasibility of implementing them with commercial transceivers in SDR platforms. A question that needs to be answered in future research is if the custom implementation of the proposed communication paradigm can result in lower power consumption and be incorporated in low cost, miniaturized sensor nodes.

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