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A Novel Approach for Quality of Video Streaming in Multimedia Wireless Sensor Networks

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ABSTRACT: Wireless multimedia sensor networking has made significant advances in both research and practice in recent years. In addition to traditional data services, content-rich multimedia applications (such as videoconferencing, VoD or VoIP) are increasingly being deployed in this type of networks. However, multimedia services need QoS support to maintain user satisfaction. This paper investigates the potential of the compressed sensing (CS) paradigm for video streaming in Wireless Multimedia Sensor Networks. The objective is to study performance limits and outline key design principles that will be the basis for cross-layer protocol stacks for efficient transport of compressive video streams. Hence, this paper investigates the effect of key video parameters (i.e., quantization, CS samples per frame, and channel encoding rate) on the received video quality of CS images transmitted through a wireless channels. It is shown that, unlike JPEG-encoded images, CS-encoded images exhibit an *inherent resiliency* to channel errors, caused by the unstructured image representation; this leads to basically *zero* loss in image quality for random channel bit error rates as high as 10 −4, and low degradation up to 10−3. Furthermore, it is shown how, unlike traditional wireless imaging systems, forward error correction is not beneficial for wireless transmission of CS images. Instead, an adaptive parity scheme that drops samples in error is proposed and shown to improve image quality. Finally, we present our initial investigations on a low-complexity, adaptive video encoder that performs low-complexity motion estimation.

Index Terms: Compressed Sensing, Wireless Multimedia Sensor Networks, Compressive Video Streaming, Video Streaming

I.INTRODUCTION

Compressed Sensing

Compressed sensing (also known as compressive sensing, compressive sampling, or sparse sampling) is a signal processing technique for efficiently acquiring and reconstructing a signal, by finding solutions to underdetermined linear systems. This takes advantage of the signal's sparseness or compressibility in some domain, allowing the entire signal to be determined from relatively few measurements.

WSN Optimization

WSN optimization is a collection of techniques for increasing data-transfer efficiencies across Wireless Sensor Networks.

WSN optimization techniques

Deduplication – Eliminates the transfer of redundant data across the WSN by sending references instead of the actual data. By working at the byte level, benefits are achieved across IP applications.
Compression – Relies on data patterns that can be represented more efficiently. Essentially compression techniques similar to ZIP, RAR, ARJ etc. are applied on-the-fly to data passing through hardware (or virtual machine) based WSN acceleration appliances
Latency optimization – Can include TCP refinements such as window-size scaling, selective Acknowledgements, Layer 3 congestion control algorithms, and even co-location strategies in which the application is placed in near proximity to the endpoint to reduce latency.[6] In some implementations, the local WSN optimizer will answer the requests of the client locally instead of forwarding the request to the remote

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server in order to leverage write-behind and read-ahead mechanisms to reduce WSN latency

Forward error correction – mitigates packet loss by adding an additional loss-recovery packet for every "N" packets that are sent, and this would reduce the need for retransmissions in error-prone and congested WSN links.

Connection limits – Prevents access gridlock in routers and access points due to denial of service or peer to peer. Best suited for wide open Internet access links, can also be used on WSN links.

Simple rate limits – Prevents one user from getting more than a fixed amount of data. Best suited as a stop gap first effort for remediating a congested Internet connection or WSN

Multimedia Streaming

Streaming media is multimedia that is constantly received by and presented to an end-user while being delivered by a provider. Its verb form, "to stream", refers to the process of delivering media in this manner; the term refers to the delivery method of the medium rather than the medium itself.

Multimedia in-network processing: Processing of multimedia content has mostly been approached as a problem isolated from the network-design problem, with a few exceptions such as joint source-channel coding [44] and channel-adaptive streaming [51]. Hence, research that addressed the content delivery aspects has typically not considered the characteristics of the source content and has primarily studied cross-layer interactions among lower layers of the protocol stack. However, the processing and delivery of multimedia content are not independent and their interaction has a major impact on the levels of QoS that can be delivered. WMSNs will allow performing multimedia in-network processing algorithms on the raw data. Hence, the QoS required at the application level will be delivered by means of a combination of both cross-layer optimization of the communication process, and in-network processing of raw data streams that describe the phenomenon of interest from multiple views, with different media, and on multiple resolutions. Hence, it is necessary to develop application independent and self-organizing architectures to flexible perform in-network processing of multimedia contents.

II.RELATED WORKS

The new cross-layer optimized communication protocol stacks based on the recently proposed compressed sensing (CS) paradigm [5], [6] can offer a convincing solution to the aforementioned problems. However, as will become clearer in the following, this may require a rethinking of traditional wireless streaming functionalities across multiple layers. Compressed sensing (aka "compressive sampling") is a new paradigm that allows the faithful recovery of signals from far fewer measurements than traditional methods based on Nyquist sampling. Hence, CS can offer an alternative to traditional video encoders by enabling imaging systems that sense and compress data simultaneously and much faster, *at very low computational complexity for the encoder*. Image coding and decoding based on CS has been recently explored [9]. So-called single-pixel cameras that can operate efficiently across a much broader spectral range (including infrared) than conventional silicon-based cameras have also been proposed [1]. However, transmission of CS images and video streaming in wireless networks, and their statistical traffic characterization, are substantially unexplored.

III. PROPOSED SYSTEM

In this paper, we study the potential of compressive video streaming for Wireless Multimedia Sensor Networks by conducting a cross-layer performance evaluation of wireless streaming of CS video on resource constrained devices. Our objective is to study performance limits and outline key design principles that will be the basis for cross-layer protocol stacks designed for efficient transport of compressive video streams over multi-hop wireless networks. Our contributions can be outlined as follows:

- We study the effect of key video parameters (i.e., quantization, CS samples per frame, and channel encoding rate) on the received video quality of CS images transmitted through a wireless channels.
- We show how, unlike JPEG-encoded images, CS-encoded images exhibit an *inherent resiliency* to channel errors, caused by the unstructured image representation; this leads to basically *zero* loss in image quality for random channel bit error rates as high as 10−4, and low degradation up to 10−3. We discuss the profound impact of this finding on wireless protocol design.
- Show how, unlike traditional wireless imaging systems, forward error correction is not beneficial in CS images at levels of bit error rate as high as 10−2. Instead, we propose an adaptive parity scheme that drops samples in error, thus improving the quality of the image reconstruction process.

System Architecture

Compressed Sensing Preliminaries

We consider an image signal represented through a vector $\mathbf{x} < RN$, where N is the vector length. We assume that there exists an invertible $N \times N$ transform matrix $\mathbf{\Psi}$ such that

$$\mathbf{x} = \mathbf{\Psi s}$$

where $\mathbf{s}$ is a K-sparse vector, i.e., $||s||0 = K$ with $K < N$, and where $||\ \cdot\ ||p$ represents p-norm. This means that

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theimage has a sparse representation in some transformed domain, e.g.,wavelet. The signal is measured by taking $M < N$ measurements from linear combinations of the element vectors through a linear measurement operator $\mathbf{\Phi}$. Hence,

$$\mathbf{y} = \mathbf{\Phi x} = \mathbf{\Phi\Psi s} = \tilde{} \mathbf{\Psi s}.$$

We would like to recover $\mathbf{x}$ from measurements in $\mathbf{y}$. However, since $M < N$ the system is underdetermined. Hence, given a solution $\mathbf{s0}$ to (2), any vector $\mathbf{s}*$ such that $\mathbf{s}* = \mathbf{s0} + \mathbf{n}$, and $\mathbf{n} \in N(\tilde{}\mathbf{\Psi})$ (where $N(\tilde{}\mathbf{\Psi})$ represents the null space of $\tilde{}\mathbf{\Psi}$), is also a solution to (3). However, it was proven in [6] that if the measurement matrix $\mathbf{\Phi}$ is sufficiently incoherent with respect to the sparsifying matrix $\mathbf{\Psi}$, and K is smaller than a given threshold (i.e., the sparse representation $\mathbf{s}$ of the original signal $\mathbf{x}$ is "sparse enough"), then the original $\mathbf{s}$ can be recovered by finding the sparsest solution that satisfies (2), i.e., the sparsest solution that "matches" the measurements in $\mathbf{y}$. However, the problem above is in general NP-hard. For matrices $\tilde{}\mathbf{\Psi}$ with sufficiently incoherent columns, whenever this problem has a sufficiently sparse solution, the solution is unique, and it is equal to the solution of the following problem:

$$P_1 : \ minimize \ ||s||_1$$
$$subject\ to : ||\mathbf{y} - \tilde{\mathbf{\Psi}}\mathbf{s}||_2^2 < \epsilon,$$

Where ϵ is a small tolerance. Note that problem $P1$ is a convex optimization problem. The reconstruction complexity equals $O(M^2N^{3/2})$ if the problem is solved using interior point methods [2].

Video Model

We represent each frame of the video by 8-bit intensity values, i.e., a grayscale bitmap. To satisfy the sparsity requirement of CS theory, the wavelet transform is used as a sparsifying base. A conventional imaging system or a single-pixel camera [1] can be the base of the imaging scheme. In the latter case, the video source only obtains random samples of the image (i.e., linear combinations of the pixel intensities). In our model, the image can be sampled using a scrambled block Hadamardensemble [3]

$$\mathbf{y} = \mathbf{H}_{32} \cdot \mathbf{x},$$

Where $\mathbf{y}$ represents image samples (measurements), $\mathbf{H32}$ is the 32 × 32 Hadamard matrix and $\mathbf{x}$ the matrix of the image pixels. The matrix $\mathbf{x}$ has been randomly reordered and shaped into a 32 × N 32 matrix where N is the number of pixels in the image. Then M samples are randomly chosen from $\mathbf{x}$ and transmitted to the receiver. The receiver then uses the M samples transmitted along with the randomization patterns for both randomizing the pixels into $\mathbf{x}$ and choosing the samples out of x to be transmitted (both of which can be decided upon before network setup) and recreates the image solving $P1$ in (3) through a suitable algorithm, e.g., GPSR2 [4], StOMP

Transmission of Infra Frame Encoded Video

We study the effect of key design parameters on the received video quality of CS images transmitted through a wireless channels; We first consider intra-coded frames, i.e., we temporarily ignore the temporal correlation among different frames. For a given data rate at the transport layer F [*bit/s*], number of frames per second, and end-to-end bit error rate (BER), there are three main parameters that determine the perceptual quality of the received video frame, i.e., the quantization level of each sample Q, the number of samples per frame M, and the channel encoding rate R.

1)Sample Quantization Rate

The *sample quantization rate*Q [*bit/sample*] is the number of bits used to quantize eachsample. The smaller Q, the lower the amount of information sent per sample, and therefore the greater the number of samples that can be transmitted for a target data rate F, at the expense of greater quantization distortion in each sample. We empirically evaluated the video quality of CS images against the optimal ratio of number of samples M vs quantization rate Q. To do so, we evaluated the *Structural Similarity Index* (SSIM)3 [6] between the original and the encoded image for a standardized set of 25 images. We kept the total image size constant at 37% of the original image size, i.e., the image size that allows sending N samples (where N corresponds to the number of image pixels) with 3-bit quantization.

Figure 1 shows the average SSIM of the above mentioned images against sample quantization rate, with 95% confidence intervals. Clearly, *the benefit of more samples outweighs the distortion caused be less accurate samples* down to 5bit/sample. Intuitively, this is because the recovery algorithm finds *image with the sparsest transform* that minimizes the difference between the samples received and the samples generated from the reconstructed image. This means that even though a small amount of samples (less than one in 103) may be corrupted, the reconstructed image is the same or very similar to the image which would have been reconstructed without bit errors.

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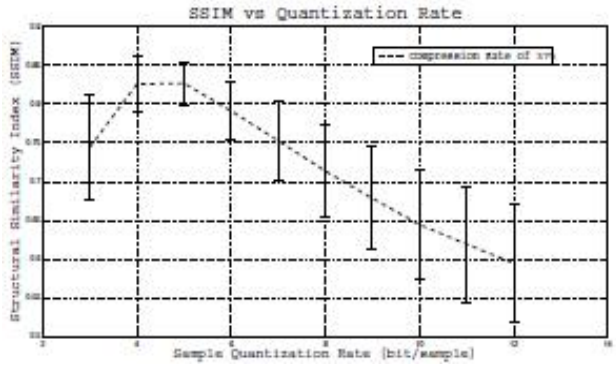

Fig. 1. Structural Similarity (SSIM) Index [16] for Images with a Constant Bit Rate of 37% of the Original Image Size for Varying Quantization Levels.

2) Samples per Frame

The number of samples N needed to reconstruct the image to a predefined quality level is dependent on the sparsity of the transmitted image. The greater the number of transmitted samples compared to the sparsity of the image, the better the image quality of the received frame. Depending on the desired video quality at the receiver, the maximum number of samples per frame can be selected to achieve that quality.

3) Effect of Channel Errors

In CS, the transmitted samples constitute a random, incoherent combination of the original image pixels. This means that, unlike traditional wireless imaging systems, in CS no individual sample is more important for image reconstruction than any other sample. Instead, *the number of correctly received samples* is the only main factor in determining the quality of the received image. Also, a small amount of random channel errors does not affect the perceptual quality of the received image *at all*, since, for moderate bit error rates, the greater sparsity of the "correct" image will offset the error caused by the incorrect bit. This is demonstrated in Fig. 3. For any BER lower than 10−4, there is *no noticeable drop in the image quality*. Up to BERs lower than 10−3, the SSIM is above 0.8, which is an indicator of good image quality. CS image representation is completely *unstructured*: this fact *makes CS video much more resilient than existing video coding schemes to random channel errors*. This has important consequences and *provides a strong motivation for studying* compressive wireless video streaming in WMSNs.

To determine the *channel encoding rate*, we first must determine the channel coding strategy appropriate for compressed sensed imaging data transmitted over a multi-hop wireless network. One of the biggest advantages of compressed sensing is that the transmitted samples constitute a random, incoherent Combination of the original data. This means that no single sample is any more important than any other sample. Instead, only *the number* of correctly received samples is the main factor in determining the quality of the received image. Also, following the same logic as for the quantization parameter selection, a small amount of errors will not considerably affect the perceptual quality of the received image, since, for a moderate error rate, the greater sparsity of the correct image will offset the error caused by the incorrect bit. This is demonstrated in Figs 3 and 4. In Fig. 3, the same set of images were reconstructed both with and without corrupted samples after being transmitted through a binary symmetric channel.Clearly, the image quality considerably improves when the corrupted samples are dropped.

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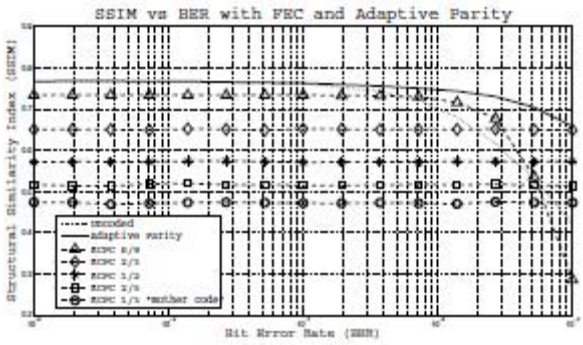

Fig. 2. Adaptive Parity vs RCPC Encoding for Variable Bit Error rates

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Fig. 3. Lena Image with CS (above) and JPEG (below) for BER (a) 10−5 (b) 10−4 (c) 10−3.

Adaptive Parity – Based Channel Coding

For a fixed number of bits per frame, the perceptual quality of video streams can be further improved by dropping errored samples that would contribute to image reconstruction with incorrect information. This can be obtained by using even parity on a predefined number of samples, which are all dropped at the receiver or at an intermediate node if the parity check fails. This is particularly beneficial in situations when the BER is still low, but too high to just ignore errors. To determine the amount of samples to be jointly encoded, the amount of correctly received packets is modeled as

$$C = \left(\frac{Q \cdot b}{Q \cdot b + 1}\right)(1 - BER)^{Q \cdot b + 1},$$

Where C is the estimated amount of correctly received samples, b is the number of jointly encoded samples, and Q is the quantization rate per sample. To determine the optimal value of b for a given BER, (5) can be differentiated, set equal to zero and solved for b. If the end-to-end BER can be estimated by the transmitting node, the optimal channel encoding rate can then be chosen and used to encode the samples. The received video quality using the parity scheme described was compared to different levels of channel protection using rate compatible punctured codes (RCPC). Specifically, we use the 1 4 mother codes discussed in [7]. Briefly, a 1 4 convolution code is punctured to decrease the amount of redundancy needed for the encoding process. These codes are punctured progressively so that every *higher rate* code is a subset of the lower rate codes. For example, any bits that are punctured in the 4 15 code must also be punctured in the 1 3 code, the 4 9 code, an so on down to the highest rate code, in this case the 8 9 code. Because of this setup, the receiver can decode the entire family of codes with the same decoder. This allows the transmitter to choose the most suitable code for the given data. Clearly, as these codes are punctured to reduce the redundancy, the effectiveness of the codes decreases as far as the ability to correct bit errors. Therefore we are trading bit error rate for transmission rate.

Figure 2 shows the adaptive parity scheme compared to RCPC codes. Clearly, for all reasonable bit error rates, the adaptive parity scheme outperforms all levels of RCPC codes. The parity scheme performs better for all levels of BER, and it is also much simpler to implement than more powerful forward error correction (FEC) schemes. The parity scheme performs better because, even though the FEC schemes show stronger error correction capabilities, the additional overhead does not make up for the video quality increase compared to just dropping the samples which have errors.

Inter Frame Encoded Compressed Video Streaming

In this section, we discuss a method for inter-frame encoding. While this initial investigation is general, it works particularly well for security videos. Security videos are a special case of video in which we can assume that the camera is not moving, but only the objects within the field of view (FOV) of the camera are moving. Because of this, there will often be a large amount of redundancy from one frame of the video to the next. One way to exploit this redundancy within the framework of compressed sensing is by taking the algebraic difference between two frames, encoding this difference, recreating an image representing this difference and combining it with the reference frame at the receiver.

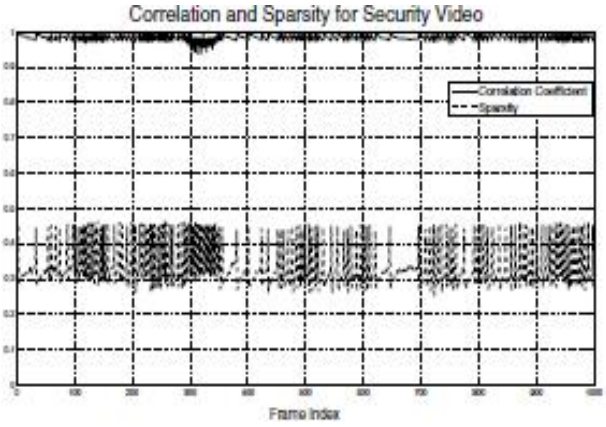

Figure 4 : Correlation and Sparsity for a Security Video

The amount of sparsity in the difference image can be estimated based on the correlation, as shown in Fig. 4. In this figure, we show the amount of correlation between the two frames being considered, the amount of sparsity as measured at the decoder and the quality (SSIM) of the decoded frame as compared to the original uncompressed frame. The”spikes” in the

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sparsity value indicate place where the intra-frame compression was used. In the sections without those spikes, clearly there is a negative linear relationship between the two. Since the correlation can be measured using only information at the video source, this allows the source node to estimate the amount of sparsity at the receiver.

If the image being encoded and the reference image are very similar (i.e. have a very high correlation coefficient), then this difference image will be sparser than either of the original images, and can therefore be transmitted at the same quality using fewer samples than the original image.

VI.CONCLUSIONS

We have investigated the potential of the compressed sensing (CS) paradigm for video streaming in WMSNs. We have shown that, unlike JPEG-encoded images, CS-encoded images exhibit an *inherent resiliency* to channel errors, caused by the unstructured image representation; this leads to basically *zero* loss in image quality for random channel bit error rates as high as 10−4, and low degradation up to 10−3. Furthermore, we have shown that, unlike traditional wireless imaging systems, forward error correction is not beneficial for wireless transmission of CS images. Instead, we proposed an adaptive parity scheme that drops samples in error thus improving the quality of the reconstructed image. Finally, we have proposed a low-complexity adaptive video encoder that performs motion estimation on the video sensors, thus considerably reducing the amount of data to be transmitted. Our future work will be focused on designing cross-layer optimized communication protocols for CS-based WMSN based on the principles outlined in this preliminary investigation.

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