RA-CVS: Cooperating at Low Power to Stream Compressively Sampled Videos

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***Abstract*—Video streaming applications are becoming increasingly popular as low priced video-enabled mobile devices (such as smart phones) become more common. However, traditional video streaming systems are not designed for mobile devices, and require both high computational complexity at the video sensor and very high channel quality to achieve good performance. Our recently proposed compressive video sensing (CVS) video streaming system is a low complexity, low power compressed-sensing-based encoder designed to address these challenges. However, even using CVS, the energy consumption of multimedia sensors is still much higher than that of traditional scalar sensors.**

In this article, we present a cooperative relay-assisted compressed video sensing (RA-CVS) system that takes advantage of the error resilience of video encoded using CVS to maintain good video quality at the receiver while significantly reducing the required SNR, and therefore the required transmission power at the multimedia sensor node. This system uses the natural error resilience of CS encoded video signals to design a cooperative scheme that *directly reduces the mean squared error (MSE)* of the reconstructed CS samples representing a video frame, which allows the receiver to correctly reconstruct the video even at very low SNR levels. The proposed system is tested using both simulation and USRP2 testbed evaluation and is shown to outperform traditional cooperative systems in terms of received video quality as a function of channel SNR.

I. Introduction

Advances in sensing, computation, storage, and wireless networking are driving an increasing interest in multimedia [1], [2] and *participatory* [3] sensing applications. While these applications show high promise, they require wirelessly networked streaming of video originating from devices that are constrained in terms of instantaneous power, energy storage, memory, and computational capabilities. Predictive video encoding, specifically MPEG-4 Part 2, H.264/AVC [4] and H.264/SVC [5], has been one of the major factors in enabling these applications because of superior rate-distortion characteristics and higher error resiliency than previous video encoders.

However, H.264 is known to be far from ideal for resource-constrained devices. This is mainly due to the energy required to encode, the complexity of the H.264 encoder and the relatively low bit error tolerance [6]. In [7], we looked at the problem from a different perspective and introduce a video encoder based on compressed sensing which we refer to as compressed video sensing (CVS). CVS encodes video based on simple linear, non-processing-intensive operations, leading to low power consumption and processor load. The video representation enabled by CVS *is inherently resilient to channel errors* - a few channel errors do not affect the image representation at all, and more severe impairments of the wireless channel can be effectively combated with simple error detection mechanisms such as adaptive parity. Third, since compressed sensing operates on pseudo-random sampling matrixes, the video source information is distributed over measurements of equal significance. Therefore, a sample lost because of channel errors can be replaced by any other measurement. Hence, the video quality increases and decreases with the number of received measurements regardless of which measurements are received. For multicast transmissions, this means that a client with a better channel (or in a less congested portion of the network) can receive higher quality video than a client with poorer channel quality (or experiencing more severe congestion), thus making CVS inherently scalable.

CVS offers significant promise on its own in that it is low-complexity, resilient to channel errors and scalable to within a single sample. However, it does not fully leverage the error-resilience properties of compressed sensing, which could potentially help even further decrease the impact of channel errors. In this paper, we ask the following fundamental question: *"Can we leverage the unique properties of the signal representation of compressively sampled videos to develop cooperative wireless networking schemes to stream video at high quality (or, equivalently, to decrease the energy consumption for a target video quality) over resource constrained devices (e.g., video sensor networks)"*? To address this question, we develop and study a new cooperative streaming system based on compressed sensing named relay assisted compressive video sensing (RA-CVS). RA-CVS is a new cooperative networking scheme that leverage properties of CS image representation by cooperatively reconstructing the signal *in the domain of compressed samples*. By minimizing the mean squared error (MSE) in the reconstructed real domain samples, compared to traditional methods that attempt to merely correct "errored" bits, we demonstrate that we can significantly reduce the SNR required for successful video transmission.

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II. Compressed Video Sensing (CVS)

CVS [7] uses compressed sensing to take advantage of both the spatial correlation within a frame (intra-frame) and the temporal correlation between frames (inter-frame). For intra-frame encoding, a frame is represented by a vector $\mathbf{x} \in R^N$. We assume that there exists an invertible $N \times N$ transform matrix $\mathbf{\Psi}$ such that

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

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 the image 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,

$$\mathbf{y} = \mathbf{\Phi x} = \mathbf{\Phi \Psi s} = \tilde{\mathbf{\Psi}}\mathbf{s}. \tag{2}$$

Although, in general, $\mathbf{x}$ can not be recovered directly, [8] shows 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 "matches" the measurements in $\mathbf{y}$, i.e., by solving the optimization problem

$$\begin{aligned} &\underset{\mathbf{s}}{\text{minimize}} && ||\mathbf{s}||_1 \\ &\text{subject to:} && ||\mathbf{y} - \tilde{\mathbf{\Psi}}\mathbf{s}||_2^2 < \epsilon, \end{aligned} \tag{3}$$

where ϵ is a small tolerance. Note that problem (3) is a convex optimization problem [9].

To exploit inter-frame redundancy within the framework of compressed sensing, we take the algebraic difference between the CS samples. Then, this difference is *again compressively sampled* and transmitted. 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 and have less variance than either of the original images, and can therefore be transmitted at the same quality using fewer samples and fewer bits per pixel than the original image. For a full explanation of CVS video encoding, the reader is referred to [7], and for a comparison between CVS and traditional video encoding for sensor networks, the reader is reffered to [6].

III. Relay Assisted Compressed Video Sensing (RA-CVS)

While the CVS encoder presented in [7] is much better than traditional video encoders for WMSNs, the energy consumption is much higher than what is required for scalar sensor networks. With this in mind, we now show how the natural error resilience of CS encoded video, along with spatial diversity, can be used to design a relaying system that requires only a fraction of the energy required for traditional transmission schemes. Unlike traditional cooperative systems that leverage channel diversity to attempt to *reduce the bit error rate*, we design a cooperative scheme that *directly reduces the mean squared error (MSE)* of the reconstructed CS samples representing a video frame. The approach is substantially different and is motivated, as will be shown later, by the specific and unique nature of CS encoded video signals and by its natural error resilience of to small magnitude errors.

A. Reconstructing Real-valued CVS Samples

In CS-based imaging, the wavelet-transformed video frames are sparse, and can therefore be reconstructed using CS. In this section, we examine how the *sparsity of channel errors* can be used to develop an error resilient video streaming system.

CS-based Error-resilient Transmission. In [10], Candes formalized the intuitive idea that CS can be used to combat channel errors. Since errors are generally sparse (i.e., very few of the received symbols are typically corrupted by noise), the *sparse error vector* can be reconstructed using a compressed sensing reconstruction algorithm. To determine which received symbols contain errors, the source must create a set of linear combinations of the CVS samples that adds redundancy with respect to the original set of CVS samples, which we will refer to as error resilient CS (ERCS) samples. We can think of this as creating additional error correction samples to combat the channel errors.

Explicitly Correcting Bit Errors May Be Unnecessary. While detecting channel errors by solving this sparse reconstruction problem may work well in principle, the number of ERCS samples required to correct bit errors over a *quantized* signal (e.g., a quantized version of the CVS samples) can be very high. There are two important reasons for this. First, since ERCS multiplication is done in the real domain, we need to quantize the ERCS samples. If the CVS encoded samples are already quantized, this process adds additional quantization noise to the signal, degrading the performance of the reconstruction algorithm and requiring additional samples to accurately reconstruct the received signal. Second, rather than correcting errors on the transmitted bits, as in traditional error correction schemes, errors in ERCS encoded samples are corrected at the sample level. This means that, depending on which bit is flipped, the magnitude of the error in the sample could be anywhere from a single quantization level (if the least significant bit (LSB) is flipped) to half of the magnitude range of the signal (if the most significant bit (MSB) is flipped). Removing all of the bit errors requires getting every reconstructed sample *exactly correct*. This may require excessive overhead if only the LSB was flipped, as the magnitude of the incorrect samples is very close to the quantization error in that sample.

The good news, however, is that for the purpose of our application *correcting each and every bit affected by channel errors is in fact unnecessary*. In the example above, if the magnitude of a sample error is close to the quantization noise, it will not have a significant impact on the reconstructed quality, or on the mean squared error of the reconstructed CVS samples. We can essentially ignore these types of errors, and the reconstructed quality of the video will not be noticeably affected.

We can therefore avoid both the problem with additional quantization noise and with wasting resources finding inconsequential errors by using the *real valued* (unquantized) CVS samples to create the ERCS samples. This clearly avoids the quantization errors, reducing the quantization noise in the signal. Perhaps more importantly, we can use the MSE of the reconstructed video samples as the performance metric of the system, rather than the bit error rate of the ERCS samples. The MSE performance not only better reflects the video quality, but it will naturally weight the significance of the small scale errors less than more important (i.e., larger magnitude) errors. Finally, since CS reconstruction quality depends on the MSE of the received signal, we show below that we can still achieve the same performance *as if we had received the quantized version of the signal perfectly*.

Specifically, we create a CVS encoded vector $\mathbf{y} \in \mathbb{R}^M$ that represents a video frame we would like to transmit on a channel with very low SNR. Instead of transmitting $\mathbf{y}^{(Q)}$ which is the Q-quantized version of $\mathbf{y}$, we instead create a vector $\mathbf{w} = A\mathbf{y}$ where $A \in \mathbb{R}^{L_A \times M}$ is the ERCS sampling matrix and has the same properties as Φ in Section II except, since $L_A > M$, we are creating additional redundant samples. We then transmit $\mathbf{w}^{(Q)}$, which is the Q-quantized version of $\mathbf{w}$. The received signal, corrupted by noise, can then be modeled as $\hat{\mathbf{w}} = A\mathbf{y} + \mathbf{e}$, where $\mathbf{e}$ is a *sparse* error vector. The original CVS encoded vector $\hat{\mathbf{y}}$ can be reconstructed by solving the convex minimization problem

$$\text{minimize } ||A\mathbf{y} - \hat{\mathbf{w}}||_1, \tag{4}$$

which can be interpreted as finding the transmitted signal corrupted by the sparsest error vector that matches the received data.

Since $\mathbf{y}$ is kept in the real domain, and CS encoded video is resilient to small scale errors, increasing the number of redundant samples created by the ERCS matrix multiplication will decrease the mean squared difference between the reconstructed $\hat{\mathbf{y}}$ and the original $\mathbf{y}$. The objective of the streaming protocol is then to choose the ERCS sampling matrix such that

$$\|\hat{\mathbf{y}} - \mathbf{y}\|_2^2 \le \epsilon \tag{5}$$

is satisfied, where ϵ is an MSE threshold below which the received video quality is acceptable. For example, if

$$\epsilon = \|\mathbf{y}_{\mathbf{Q-bit}} - \mathbf{y}\|_2^2, \tag{6}$$

where $\mathbf{y}_{\mathbf{Q-bit}}$ is the Q bit quantized version of $\mathbf{y}$ then, if (5) holds, the recovered signal will have the same quality *as if the quantized signal had been received perfectly*.

As we have been stressing, this technique for protecting CS encoded samples through ERCS matrix multiplication is particularly effective because of the real-valued nature of the original CVS encoded video signal $\mathbf{y}$ and because, in general, CS reconstruction is very resistant to low power noise [11]. To see this, suppose we have a set of measurement samples $\mathbf{y}^{\#} =$

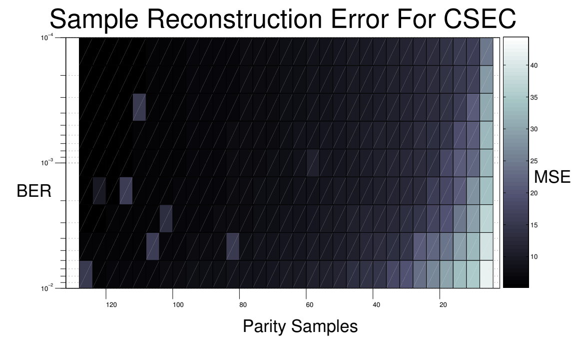

Fig. 1. ERCS sampled reconstruction error.

$\Phi\mathbf{x} + \mathbf{n}$ corrupted by noise, where $\mathbf{n}$ is a deterministic noise term, and is bounded by $\|\mathbf{n}\|_2 < \epsilon$. As long as Φ is incoherent with respect to the sparsifying matrix, then the value of $\mathbf{x}^{\#}$ reconstructed using (3) from $\mathbf{y}^{\#}$ will be within

$$\|\mathbf{x}^{\#} - \mathbf{x}\| \le C \cdot \epsilon, \tag{7}$$

where C is a "well behaved" constant[1].

It is easy to see why $\Phi\mathbf{x}^{\#}$ will be within 2ϵ of $\Phi\mathbf{x}$ using the triangle inequality. Specifically,

$$\|\Phi\mathbf{x}^{\#} - \Phi\mathbf{x}\|_2 \le \|\Phi\mathbf{x}^{\#} - \mathbf{y}\|_2 + \|\Phi\mathbf{x} - \mathbf{y}\|_2 \le 2\epsilon. \tag{8}$$

To determine the magnitude of the error in the reconstructed video samples, an empirical study is presented in Fig. 1, where we show the reconstruction error for a typical CS error correction system for bit error rates ranging from 10^{-4} to 10^{-2} in the ERCS samples. The colormap to the right shows the color relation to the MSE and the horizontal axis shows the number of additional samples added. To create Fig. 1, 128 sample blocks of a test image were encoded, quantized, transmitted through a binary symmetric channel and reconstructed using (3). The darker areas of the graph are regions where the reconstructed signal satisfies (6). Figure 1 shows that for BER rates less than 10^{-2} in the ERCS samples, only a 32% overhead is required to satisfy (6).

B. Relay Assisted CVS Sample Reconstruction

The ERCS system defined above works well in a simple binary symmetric channel, or even an AWGN channel. However, when the transmission power is low, severe fading can cause the loss of far too many samples for any ERCS matrix to correct. In this section, we introduce a new relaying strategy that allows sensors to transmit video at SNR values that are a fraction of traditional cooperative relaying systems without sacrificing video quality, thus enabling extra low-power sensors. Consider the system topology shown in Fig. 2, where S is the source node, R_i is relay node i and D is the destination. h_{SD}, h_{SR_i} and h_{R_iD} represent the channel coefficients between S and D, S and R_i and R_i and D respectively. To combat channel errors between S and D, we would expand the CVS samples using an ERCS matrix

[1]For practical systems, C is a small constant between 5 and 10 [11].

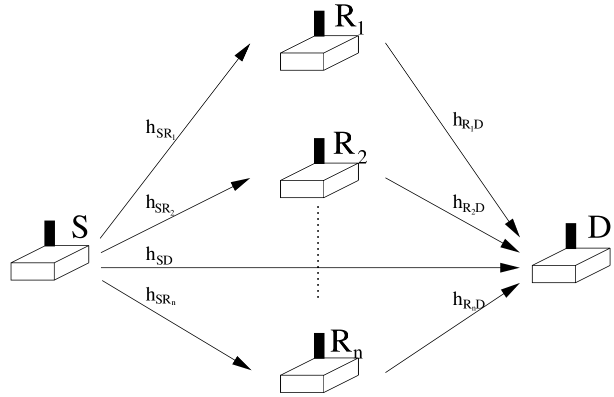

Fig. 2. Cooperative relaying model.

enough to correct any errors on the source-destination channel. However, if the channel is very poor quality, the number of samples required to correct a large number of errors may be very high. We can potentially reduce the number of required ERCS samples by taking advantage of relay nodes available between the source and destination that could be able to reconstruct the relay assisted CVS (RA-CVS) samples using far fewer samples than what would be required otherwise.

First, basic ERCS encoding (without cooperation) is used to correct errors on the source-relay transmission. Assume the source node transmits L_A samples, defined as

$$L_A \geq (SER_{SR_i} \cdot L_A)\log M, \quad \forall i \leq n \tag{9}$$

where SER_{SR_i} is the sample error rate over the source-relay channel. As long as (9) is satisfied, there will be enough samples to reconstruct the signal [8]. Each relay then transmits L_{B_i} samples, where L_{B_i} is such that

$$\sum_{i=1}^{n} L_{B_i} \geq \left[(SER_{SD} \cdot L_A) + \left(\sum_{i=1}^{n} SER_{R_iD} \cdot L_{B_i} \right) \right] \log M, \tag{10}$$

where SER_{R_iD} is the sample error rate over the i^{th} relay-destination channel and SER_{SD} is the sample error rate over the source-destination channel. The signals at the receiver can then be expressed as

$$\begin{aligned} \mathbf{w_{R_i}} &= h_{SR_i}\, A\, \mathbf{y} + \mathbf{z_{SR_i}}, \qquad i = 1, \ldots, n \\ \mathbf{w_D} &= h_{SD}\, A\, \mathbf{y} + \mathbf{z_{SD}}, \\ \mathbf{w_{D_i}} &= h_{R_iD}\, B_i\, \hat{\mathbf{y}}_{\mathbf{R_i}} + \mathbf{z_{R_iD}}, \quad i = 1, \ldots, n, \end{aligned} \tag{11}$$

where $A \in \mathbb{R}^{L_A \times M}$ and $B_i \in \mathbb{R}^{L_{B_i} \times M}$ are normalized random Gaussian matrices, and $\hat{\mathbf{y}}_{\mathbf{R_i}}$ is the solution to the optimization problem in (4) for node i.

As stated above, the relay can find $\hat{\mathbf{y}}$ from $\mathbf{w_{R_i}}$ using (4), even when $\mathbf{w_{R_i}}$ is corrupted by noise, by solving an ℓ_1 minimization problem. The destination can then reconstruct the image samples by solving the optimization problem

$$\underset{\mathbf{y}}{\text{minimize}}\ ||C\mathbf{y} - \hat{\mathbf{w}}||_1, \tag{12}$$

where

$$C = \begin{bmatrix} A \\ B_1 \\ B_2 \\ \vdots \\ B_n \end{bmatrix} \quad \mathbf{w} = \begin{bmatrix} \mathbf{w_D} \\ \mathbf{w_{D_1}} \\ \mathbf{w_{D_2}} \\ \vdots \\ \mathbf{w_{D_n}} \end{bmatrix}. \tag{13}$$

While there will still be errors in the signal transmitted from S to each R, and from each R to D, the above system will greatly reduce the number of errors, which will therefore decrease the total number of additional samples required to achieve a target MSE tolerance at the receiver.

IV. Performance Evaluation

Relay-assisted compressive video sensing is evaluated using both USRP2 testbed evaluation and extensive simulation. In a multimedia system, the most important metric for the end user is the quality of the multimedia content received. Therefore, the goal of the experiments presented here is to determine how the proposed relay-assisted cooperative video sensing schemes affect the quality of the received video.

Since RA-CVS uses relays to reduce the number of transmitted samples, we need to compare it to other relay-based protocols for a fair comparison. In this section, we briefly introduce three basic cooperative communication protocols. For a more detailed description, the reader is referred to [12], [13].

Consider the basic topology shown previously in Fig. 2. In traditional cooperative communications, a relay node overhears the transmission between a sender and a receiver and acts as a *virtual* antenna. Similar to MIMO systems, fading coefficients for each path are assumed to be uncorrelated, and this diversity can be used to increase the video quality at the receiver using maximum ratio combining (MRC) [14].

Amplify and Forward (AF): In amplify and forward (AF) cooperation, a relay node does not make any decisions about the bits received. Instead, the relay amplifies the received signal and transmits it to the destination. In the system indicated in Fig. 2, the AF transmission can be broken up into $n+1$ time slots, with a single time slot assigned to each relay. At each relay, the signal is amplified by a factor of α and retransmitted *as is* without any decoding or detection.

Decode and Forward (DF): Decode and forward (DF) cooperation is similar to AF except the relay decodes the data before re-transmitting it. If the data can be correctly detected at the relay, then DF can essentially remove the noise from the source-relay channel.

In both AF and DF, the destination uses the signal transmitted from the source in the first time slot with the relay transmissions of the *same signal* to jointly determine the received symbols. This is done using maximum ratio combining (MRC) [14].

Adaptive Amplify/Decode and Forward (AF/DF): In AF/DF, we add parity bits into the video stream to detect errors at a relay node[2]. The major limitation of traditional cooperative relaying schemes is that the destination does not have knowledge of the source-relay channel. It is up to the relay to account for errors before relaying a signal to the destination. If the relay simply transmits incorrect data, that errored signal can increase the error rate at the receiver. Instead, AF/DF uses these parity bits in the CVS video stream to intelligently transmit the incorrect portions of the signal.

If all components pass the parity test, AF/DF becomes the standard DF cooperative system. If none of the components pass the parity test, then AF/DF becomes the standard AF system. In general, the system will be a combination of the two.

Direct Transmission (DT): Direct transmission refers to standard point-to-point transmission without including any relay node. For a fair comparison to the cooperative schemes described above, the total resource budget must be consistent between all systems. For this work, the total resource budget will be constant in terms of power per transmitted bit. For example, if the DT uses BPSK, an AF or DF relaying scheme using the same overall power including only one relay must use QPSK, while a system with three relays must use (for example) 16-QAM.

A. Simulation Evaluations

First, tests are conducted to compare the different forms of cooperation to direct transmission while keeping the total number of transmitted symbols constant. For these tests, BPSK modulation is used for direct transmission and QPSK is used for the cooperative transmission. The different cooperation schemes are then compared to each other for different numbers of relays, and different relative placement of those relays. Structural similarity (SSIM) is used to evaluate the quality of each frame of the video, and the mean value per video is presented.

Simulations are performed to compare RA-CVS to direct transmission, AF, DF and AF/DF. First, a source destination pair is defined with $10\mathrm{dB}$ SNR over $10\ \mathrm{m}$, and a relay is placed at positions along the line between the source and destination. The direct transmission uses BPSK modulation, and is compared to AF, DF and AF/DF using QPSK modulation. For RA-CVS, the source transmits 140% as many QPSK samples as the BPSK DT case, and the relay transmits the other 60%, resulting in the same number of transmitted *symbols* in all tests. Because this system does not use parity bits as the other systems do, an additional quantization bit is used when quantizing the error encoded samples. Overall, the total number of transmitted symbols is equal for all systems. The received quality of the video is measured using SSIM, and is presented in Fig. 3. The cooperative schemes perform best when the relay is close to the source, and worse when the relay moves further away from the source. This reinforces the earlier assumptions that errors at the relay have a serious negative effect on the received signal quality at the receiver.

[2]Tests were run using SoftPhy [15] instead of the parity bits, and the results were significantly below the parity bit tests, even when taking into account the additional video samples available when the parity bits were not included. Because of this, the CS parity bits are used in all tests in this paper.

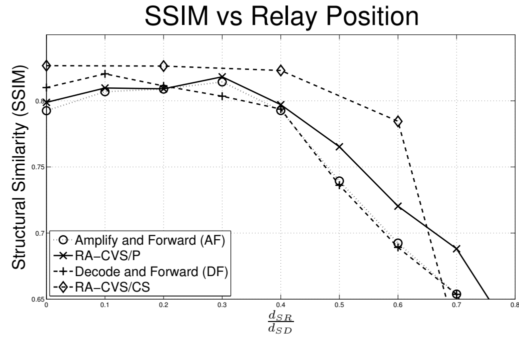

Fig. 3. Mean SSIM vs relay position.

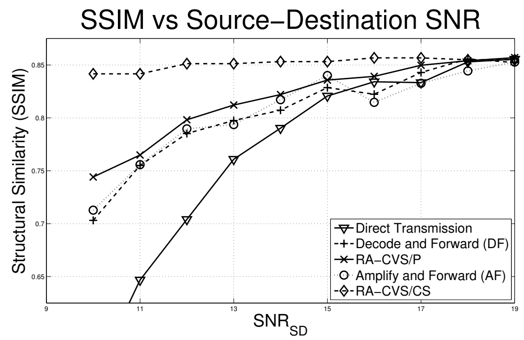

Fig. 4. Mean SSIM vs source-destination SNR.

Comparing the cooperative schemes to each other, we can see that RA-CVS performs best when the relay is close to the source. As the relay almost reaches the destination, any cooperation is detrimental because of the high losses in the source-relay channel. The reason for the sharp decrease in quality with RA-CVS is that the error at the relay is too high to be corrected by the 40% of additional samples (i.e., (9) is not satisfied). By transmitting more samples from the source instead of the relay, this could be improved for the same total number of transmitted symbols.

The second of the single relay tests is done by placing the relay directly in the center between the source and destination, and moving the source and destination incrementally away from each other. Assuming free space path loss, the source-relay and the relay-destination SNRs are always equal and exactly $6\ \mathrm{dB}$ lower than the source-destination SNR. The results of these tests are shown in Fig. 4.

In all cases, the direct transmission performs the worst, and RA-CVS performs the best, followed by AF/DF. For these tests, the source-relay channel never drops to below the level where RA-CVS can correctly decode the relay signal, so the quality of RA-CVS stays very high for all tested values. One thing to note is that, as would be expected, the benefit of using cooperation over DT decreases as the source-destination SNR increases.

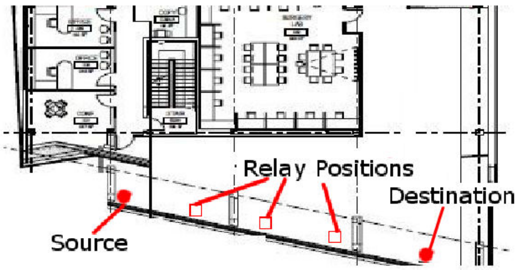

Fig. 5. Locations of Testbed Nodes.

B. Testbed Evaluation

To evaluate the protocols with realistic channels, we implement them on a USRP2 software defined radio testbed. Three USRP2 radios were used to test the received quality using direct transmission. The location of the source and destination, along with the positions of the relay node, are shown in Fig. 5. The source and destination are fixed, and the relay is placed at each of the locations shown, starting at from the closest and ending at the furthest.

The testbed results are presented in Fig. 6. The MSE of the reconstructed CVS samples is presented with the relay placed at each of the three positions. We also present results with two different versions of the RA-CVS protocol, one with only 30% of the ERCS samples generated at the source (and the other 70% generated at the relay), and the other with 80% of the ERCS samples generated at the source. Like the simulation tests, all of the protocols have the same number of total symbols transmitted between the source and relay.

For the first two relay positions, the 30% RA-CVS protocol performs best, This is because the 30% of samples are enough to correctly reconstruct the signal at the relay, and the relay is able to transmit the remaining 70% at very high quality to the destination, resulting is a large number of very good quality ERCS samples, and very low MSE in the reconstructed samples at the destination. In the 80% case, the quality is nearly constant across the three relay positions. This is because the majority of the samples are transmitted from the source directly to the destination. However, because those samples are transmitted over a very low SNR channel, the reconstructed quality is low. The quality of the traditional schemes is similar to the simulation results.

V. Conclusions and Future Work

In this paper, we present a relay assisted compressed video sensing system using compressed sensing error correction (RA-CVS). The system uses properties of compressed sensing as applied to video compression to increase the received video quality of a relay based transmission system beyond what traditional cooperation schemes can obtain. We show that RA-CVS performs better than traditional cooperative communication schemes in realistic lossy channels. Equivalently, the proposed systems require lower SNR to achieve the

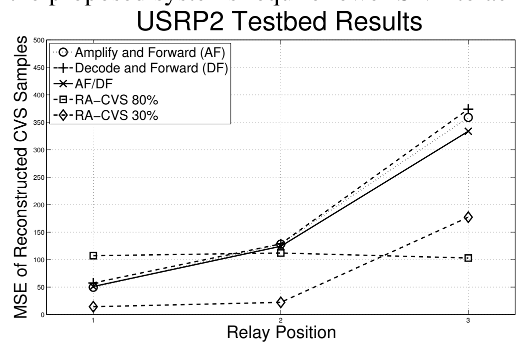

Fig. 6. MSE Results of USRP2 Testbed Evaluation.

same received video quality as traditional schemes. We then implemented the system using USRP2 software defined radios, and again demonstrated that the presented system outperform traditional cooperative communication systems.

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