Multiple-Stations Scalable Transmission with Compressed Sensing for Near Space Communication

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***Abstract*—Near Space communication suffers from communication blackout which reduces the communication quality. To solve this problem, an efficient Multiple-Stations Scalable Transmission scheme based on Compressed Sensing theory is proposed. The proposed scheme exhibits two advantages. Firstly, multiple-station receivers are disposed at different locations to accomplish continuous and real-time communication with the hypersonic vehicle. Secondly, by utilizing the *democracy* and scalability of the CS, a scalable CS-based coding method is developed in which a two-layer structure is adopted to improve the coding efficiency. Finally, simulation results show that the proposed scheme can achieve a reliable communication in the presence of data loss caused by communication interruption.**

***Index Terms*—communication, compressed sensing, scalable coding**

I. Introduction

Due to its important value in military and application, near space communication attracts the attention of researchers. Near space[1] is recognized as the atmospheric region from 20 to 100 km above the Earth's surface, and it is higher than airspace while lower than LEO. Thus, it can provide more precise information and cost efficiency than satellites, while more robust survivability than airplanes. Study of the near space has been developing, while works focus on near space communication are still insufficient, especially for the communication between hypersonic vehicle and ground stations. When the hypersonic vehicle flying across the atmosphere, a dense plasma sheath [2] is created around the vehicle and it reflects and attenuates radio waveform significantly, which causes radio blackout and results in signal loss between the vehicle and ground. In addition, the high velocity of vehicle spent ground station longer time to re-capture and re-track the vehicle to rebuild the communication, which consequently exacerbates the communication problem. A number of approaches[3][4] have been suggested for mitigation of a plasma layer to alleviate the blackout problem, including high radio frequency, high transmission power, injection of quenchants and magnetic window method. However, those approaches are devoted to reduce the attenuation of plasma sheath in physicality to improve communication condition. There is still no work present to eliminate the communication blackout or interrupt through algorithm or software implement.

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In this letter, we propose an efficient Multiple-Stations Scalable Transmission (*MSST*) scheme based on the recent Compressed Sensing (CS)[5] theory. The architecture of the proposed *MSST* scheme is fundamentally different from that of traditional transmission scheme. Specifically, multiple-station receivers, instead of a single one, are disposed at different locations, and work coordinately to accomplish continuous and real-time communication with the hypersonic vehicle. It brings a new problem about how to develop the communication strategy for the multi-receivers system, because every receiver can only get a small piece of the data.

To solve this problem, we propose a low-complex CS-based scalable coding strategy for the multi-receivers system, in which a two-layer transfer structure is adopted to further improve coding efficiency. Concretely, the signal is measured by CS and then the available CS measurements are encoded into two layers, including a base layer lossless transferring a few measurements and an enhancement layer loss transferring the reminder ones. To be specific, all bit planes of the base measurements are transferred while only a few bit planes of the enhancement measurements are transferred through discarding some high bit planes. By utilizing the correlation of CS measurements, the missing bit-planes can be predicted from a base layer. In this way, the amount of transferred measurements can be increased to further improve the reconstruction performance. Benefit from the *democracy* and scalability property of the CS, the proposed strategy is capable of eliminating the influence of data loss caused by communication interrupt. The final simulation results demonstrate the feasibility and superiority performance of the proposed scheme.

II. The Multiple-Stations Scalable Transmission Scheme

A. CS theory

Suppose signal $\mathbf{x} \in \mathbb{R}^N$ is K-sparse in some transform matrix $\mathbf{\Psi}$, so that $\mathbf{x}=\mathbf{\Psi}\boldsymbol{\alpha}$, where $\|\boldsymbol{\alpha}\|_0=K$. The signal is measured through an $M\times N$ measure matrix $\mathbf{\Phi}$ with $M<N$, and then M linear measurements can be taken.

$$\mathbf{y} = \mathbf{\Phi x} \tag{1}$$

Since $M<N$, the system is underdetermined and there are an infinite number of solutions $\mathbf{x}$ satisfying Eq.(1). To solve it, the sparsity of the signal is explored in the CS framework and the approximate solution can be obtained by solving l_1-norm minimization problem

$$\hat{\boldsymbol{\alpha}} = \arg\min \|\boldsymbol{\alpha}\|_1 \quad s.t. \quad \mathbf{y} = \mathbf{A}\boldsymbol{\alpha},\ \mathbf{A} = \mathbf{\Phi\Psi} \tag{2}$$

where $\|\boldsymbol{\alpha}\|_1 \triangleq \sum_i |\alpha_i|$. It is proved that, when the measurement matrix is random matrix and the number of measurements obeys $M=O(KlogN)$, the signal **x** can be reconstructed exactly with overwhelming probability.

Till now, properties of the compressed sensing have been investigated extensively. Firstly, CS measurements are significantly *democratic* [6], *i.e.*, each measurement carries a similar amount of information about the signal **x**. Secondly, CS is scalable, *i.e.*, the more the measurements, the better the reconstruction. Those superior properties imply that the quality of the reconstruction greatly depends only on the number of measurements and is entirely independent of which measurements are used.

Due to its equal importance, CS shares the same essence with the multiple descriptions coding, which implies that any group of CS measurements can be considered as one description of the signal. Motivated by this, two CS descriptions are highly correlated. To be specific, let $\mathbf{\Phi}_1$ be a sub-matrix consisting of multiple lines of the $\mathbf{\Phi}$, while $\mathbf{\Phi}_2$ be another

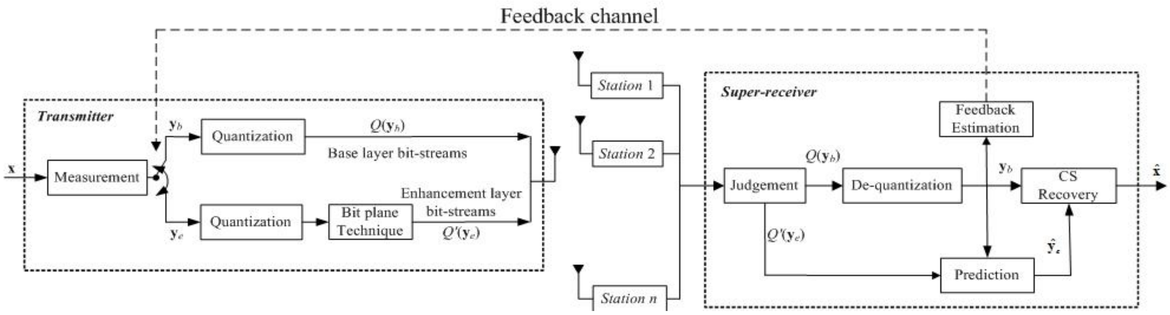


Fig.1Architecture of the proposed *MSST* scheme

different sub-matrix. Then the related measurements vectors $\mathbf{y}_1$and $\mathbf{y}_2$ can be expressed as

$$\begin{bmatrix}\mathbf{y}_1\\ \mathbf{y}_2\end{bmatrix}=\begin{bmatrix}\mathbf{\Phi}_1\\ \mathbf{\Phi}_2\end{bmatrix}\mathbf{x} \tag{3}$$

where $\mathbf{y}_1$and $\mathbf{y}_2$ represent two descriptions of the same signal. It is observed that two descriptions $\mathbf{y}_1$ and $\mathbf{y}_2$ can result in estimated $\hat{\mathbf{x}}_1$ and $\hat{\mathbf{x}}_2$, respectively. And if measurement numbers in $\mathbf{y}_1$ and $\mathbf{y}_2$ are sufficient enough, both $\hat{\mathbf{x}}_1$ and $\hat{\mathbf{x}}_2$ closely approximate to the original signal. Consequently, by exploring the correlation of $\mathbf{y}_1$and $\mathbf{y}_2$, it is feasible to estimate a rough $\hat{\mathbf{y}}_2$ from $\mathbf{y}_1$ and *vice versa*.

B. The proposed MSST communication scheme

The architecture of the proposed *MSST* scheme is illustrated in Fig.1. The *MSST* scheme is composed of three modules: a transmitter, multiple ground stations and a super-receiver. Due to vehicle's high velocity, it is really hard for the receiver to keep tracking and communicating with the vehicle in real time. To deal with this problem, multiple ground stations are sparsely disposed at different locations to progressively receive bit-streams through coordinated work. Furthermore, the interruption for near space communication is unpredictable, every stations can only get a small piece of the data. Thus the operation on each ground station is simple and institutive, *i.e.*, receiving the bit-streams and forwarding them.

At the transmitter, a CS-based scalable coding strategy is developed to compress the signal. To be specific, the signal **x** is measured by CS and then the available $\mathbf{y}=[y_1,y_2,\cdots,y_M]^T$ are divided into two sets of measurements $\mathbf{y}_b$ and $\mathbf{y}_e$, where $\mathbf{y}_b$ is lossless transferred at the base layer while $\mathbf{y}_e$ is loss transferred at the enhancement layer. Concretely, the base layer $\mathbf{y}_b$ are quantized using a fixed uniform quantizer of $\boldsymbol{B}$ bits and the resultant bit-streams $Q(\mathbf{y}_b)$ are sent. In contrast, by discarding high ($\boldsymbol{B}$-$\boldsymbol{b}$)bit planes, the enhancement bit-streams $Q'(\mathbf{y}_e)$ is composed of low $\boldsymbol{b}$ bit planes of the enhancement layer $\mathbf{y}_e$ after the same quantization. Compared with base layer, enhancement layer increases encoding efficiency greatly by throwing high bit planes and predicting at the receiver. The prediction strategy will be detailed in the subsequent. In addition, CS is scalable, which means the enhancement bit-stream can be arbitrarily truncated to fit the available channel bandwidth.

At the receiver, when receiving bit-streams, the decoder will first make a judgment of coding mode and then implement distinct process. If base layer $Q(\mathbf{y}_b)$ are received, the de-quantization is manipulated for $\mathbf{y}_b$, from which a low quality $\hat{\mathbf{x}}_l$ can be obtained. Since high bit planes of $\mathbf{y}_e$ are missing, it is difficult to directly achieve $\mathbf{y}_e$ from bit-streams $Q'(\mathbf{y}_e)$. Fortunately, $\mathbf{y}_e$ can be precisely predicted from the base layer. Finally, with the received $\mathbf{y}_b$ and predicted $\hat{\mathbf{y}}_e$, a high quality signal $\hat{\mathbf{x}}_h$ can be reconstructed.

In general, our scheme encodes signal into two layers, including a base layer of relatively lower quality signal and an enhancement layers of increasingly higher quality signal. The scalability of the CS implies that, the more $Q'(\mathbf{y}_e)$ received, the better reconstruction performance can be achieved. If part of the enhancement bit-stream could not transmitted to the decoder due to channel bandwidth fluctuations or packet losses, a slightly affect is made on the recovered signal. Thus, the proposed scheme is a fine-grain scalable transmission process. The implement of the proposed *MSST* is institutive. While there are still two issues need to be addressed. First, how to implement bit allocation between base layer and enhancement layer under a fixed bit budget. Second, how to predict enhancement $\mathbf{y}_e$ from base layer with $Q'(\mathbf{y}_e)$.

III. CRITICAL PROBLEMS

In our proposed scheme, the CS measurements are uniformly quantized with step $\boldsymbol{B}$. Let $V_{\max}=\max(|y|)$, where y represents individual CS measurement, then range $[-V_{\max},V_{\max}]$is divided into $2^{\boldsymbol{B}}$ bins. Thus the quantization step size is measured by $\Delta=2V_{\max}/2^{\boldsymbol{B}}$.

A. Rate allocation strategy

The rate allocation problem between the base layer and the enhancement layer is to minimize the overall decoded distortion at the given bit budget. [7] has demonstrated that the distortion of the quantized compressed sensing is mainly derived from quantization error and insufficiency of CS measurements, where increasing measurements and improving quantization precision are contradictory. However, the distortion in our work is more complicated since an additional enhancement layer need to be considered. Practically, for a fixed bit budget, allocating more bits (more measurements $\mathbf{y}_b$ or high quantization precision $\boldsymbol{B}$) to the base layer achieve a more accurate prediction of enhancement layer, while allocating the bit-budget to favor $\mathbf{y}_e$ are expected for enhancement layer to increase coding efficiency and better reconstruction. For simplicity, m and n represents the number of base measurements $\mathbf{y}_b$ and enhancement measurements $\mathbf{y}_e$, respectively. Then, the optimal bit allocation problem in our scheme can be addressed as a constrained optimization problem:

$$\min\left(D_b\left(m,\boldsymbol{B}\right)+D_e\left(n,\boldsymbol{b}\right)\right)\ \text{ s.t. } m\boldsymbol{B}+n\boldsymbol{b}\le N\beta, \tag{4}$$

where D_b and D_e denote the base and enhancement distortion, respectively. β is the bit rate and $N\beta$ is the bit-budget. Eq.(4) is computational intractable because the mathematical model of the distortion D_b and D_e are not independent, and multiple parameters m, n, $\boldsymbol{B}$ and $\boldsymbol{b}$ are highly related with each other. Instead, we turn to look for its asymptotic solution. Firstly, as depicted in [8], empirical studies have been conducted to test the effect of quantization of CS measurements over a set of reference images with a constant of compression rate. The optimal quantized rate for each sample is demonstrated to be 5. Thus, in this paper, we adopt the experimental results and the quantized rate $\boldsymbol{B}$ is set to be 5. Secondly, a larger $\boldsymbol{b}$ close to $\boldsymbol{B}$ will lead to the shrink of the enhancement layer, while a smaller $\boldsymbol{b}$ may also increase the difficulty of predicting $\mathbf{y}_e$. So an empirical ***b*=*ceil*(*B*/2)** is selected in the subsequent simulations, where ***ceil*** is the rounding elements to the nearest integer function towards infinity.

Table1 Rate allocation process

1. Initialization : $\ell=\mathbf{1}$, $\mathbf{y}_b^{(\mathbf{0})}=[\ ]$ and T_1;
2. Update $\mathbf{y}_b^{(\ell)}=\left[\mathbf{y}_b^{(\ell)},\mathbf{y}_\Delta^{(\ell)}\right]$ with received $\mathbf{y}_\Delta^{(\ell)}$;
3. Estimate $\hat{\mathbf{x}}_l^{(\ell)}$ and $\hat{\mathbf{y}}_b^{(\ell)}$ by Eq.(2) and Eq.(1);
4. If $\left\|\mathbf{y}_b^{(\ell)}-\hat{\mathbf{y}}_b^{(\ell)}\right\|_2^2<T_1$, stop the iteration and output m and n;

Otherwise $\ell=\ell+1$ and go to step 2.

Having selected the parameter $\boldsymbol{B}$ and $\boldsymbol{b}$, it is still quite complicated to directly solve Eq.(4) for rate allocation. In this letter, a simple alternative rate allocation is taken through feedback mechanism instead of solving Eq.(4) to obtain the optimized quality given bit-budget. To be specific, having received $\mathbf{y}_b$, the decoder performs CS reconstruction by Eq.(2) and calculates the corresponding normalized estimation error. When the estimation error is below a threshold T_1, it implies that $\mathbf{y}_b$ are sufficient enough for predicting the $\mathbf{y}_e$. Then the decoder communicates to the encoder for the transferred of the $\mathbf{y}_e$ by feedback channel shown in Fig.1. The proposed scheme provides a scalable bit stream, so that the rate allocation is operated at the decoder. The detailed allocation process is illustrated in **Table 1**.

B. *Measurement Prediction at the enhancement layer*

The prediction of the $\mathbf{y}_e$ is implemented over the $\mathbf{y}_b$ and available bit-streams $Q'(\mathbf{y}_e)$. Specifically, let integer j be the decimal number corresponding to the low $\boldsymbol{b}$ bits, for example, the decimal number j of the low bits 011 is 3. Then any enhancement measurement y encoded into $Q'(y)$ must be within the $2^{\boldsymbol{B}\text{-}\boldsymbol{b}}$ sub-interval.

$$\Omega=\bigcup_{i=-2^{B-b-1}-1}^{2^{B-b-1}-1}\left(\left(j+i\mathbf{2}^b\right)\Delta,\left(j+\mathbf{1}+i\mathbf{2}^b\right)\Delta\right), \tag{5}$$

where Ω is the collection of the feasible solutions. Based on maximum a posteriori (MAP) estimation, the feasible solution in Ω keeping the maximum posterior distribution $p\left(y|\hat{y}_l\right)$ is considered to be the correct one, where $\hat{y}_l$ is estimated by the reference $\hat{\mathbf{x}}_l$. It is equivalent to finding the minimum distance between the feasible solutions and the estimated $\hat{y}$

$$\hat{y}=\arg\max_y p\left(y|\hat{y}_l,j\right)=\arg\min_{y\in\Omega}\left|y-\hat{y}_l\right| \tag{6}$$

The pseudo code of enhancement prediction and signal reconstruction is enumerated in **Table2.**

Table2 Prediction and signal reconstruction

1. Initialization : $\ell=\mathbf{1}$, $\hat{\mathbf{y}}_e^{(\mathbf{0})}=[\ ]$;
2. Reconstruct signal $\hat{\mathbf{x}}_l$ from base $\mathbf{y}_b$ by Eq.(2);
3. Predict Enhancement $\hat{\mathbf{y}}_e^{(\ell)}$;
   (1) Receive $Q'\left(\mathbf{y}_\Delta^{(\ell)}\right)$ and calculate probability space set $\mathbf{\Omega}=\left\{\Omega_k,\ k=\mathbf{1},...,n\right\}$ by Eq.(5);
   (2) Estimate a rough $\hat{\mathbf{y}}_l$ from $\hat{\mathbf{x}}_l$ by Eq.(1);
   (3) Predict $\hat{\mathbf{y}}_e^{(\ell)}$ by Eq.(6) and update $\hat{\mathbf{y}}_e^{(\ell)}=\left[\hat{\mathbf{y}}_e^{(\ell)},\hat{\mathbf{y}}_\Delta^{(\ell)}\right]$;
4. Reconstruction $\hat{\mathbf{x}}^{(\ell)}$ from $\mathbf{y}^{(\ell)}=\left[\mathbf{y}_b\ \hat{\mathbf{y}}_e^{(\ell)}\right]$;
5. If all the measurements are received or $\left\|\hat{\mathbf{x}}^{(\ell)}\text{-}\mathbf{x}\right\|_\mathbf{2}\Big/\left\|\mathbf{x}\right\|_\mathbf{2}<\varepsilon$,

output $\hat{\mathbf{x}}=\hat{\mathbf{x}}^{(\ell)}$. Otherwise $\ell=\ell+1$ and go to step3;

Note that the calculation of the reconstruction error is impossible because the original signal is not available at the decoder. [9] provides a feasible way by taking into account the comparison between the received $\mathbf{y}_b$ and the estimated $\hat{\mathbf{y}}_b$. Concretely, the decoder performs CS reconstruction over the received $\mathbf{y}_b$ to achieve a low quality $\hat{\mathbf{x}}_l$, with which an estimated $\hat{\mathbf{y}}_b$ is obtained through Eq.(1). Then we calculate the mean square error (*MSE*) between $\mathbf{y}_b$ and $\hat{\mathbf{y}}_b$. If the *MSE* is up a threshold T_2, the decoder will receive another group of measurements, and the transmission-calculation process is repeated until the calculated *MSE* is below T_2**.** In our scheme, the rate allocation and enhancement estimation are close relationship with the parameters $\{\boldsymbol{B}, \boldsymbol{b}, T_1, T_2\}$. Different results can be obtained by assigning varied parameters.

IV. SIMULATION AND SIMULATION ANALYSIS

Numerical simulations are conducted to validate the effectiveness of proposed scheme, where 8b/pixel gray scale remote sensing images of size 256×256 are considered for test.

The total variation (TV) based algorithm [10] is adopted to perform signal reconstruction. In addition, parameters $\{\boldsymbol{B}, \boldsymbol{b}, T_1, T_2\}$ are empirically set to be {5, 3, 8, 0.01}, respectively.

(a) (b) (c)

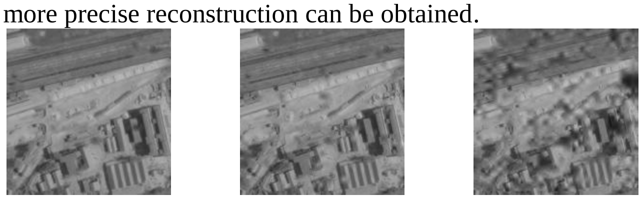
Fig.2. Test images of size256x 256

Simulation 1 is conducted to verify the feasibility of the proposed CS-based scalable coding technique (Proposed for short), where conventional CS-based coding technique (CS for short) is engaged for comparison. Suppose β is fixed as 1.0*bpp* and the communication is stable. Fig.2 lists all the test remote images, and **Table3** enumerates the resulting PSNRs

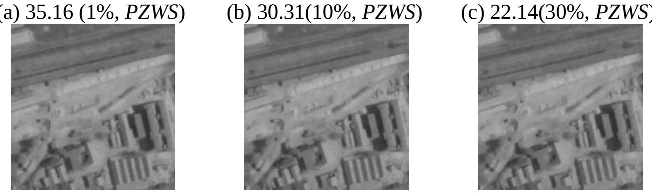
Table3 PSNR results of test images

Images	(a)	(b)	(c)	Average
CS(dB)	28.18	31.85	35.54	**31.86**
Proposed(dB)	29.70	33.58	37.13	**33.47**
Gain(dB)	**1.52**	**1.73**	**1.59**	**1.61**

As shown in Table.3, the proposed technique significantly outperforms conventional CS technique, and it achieves an average PSNR gain of up to **1.61**dB over CS technique. The superiority is mainly derived from the adopted base and enhancement layers structure. At a fixed bit budget, more measurements of the image are coded and transferred by the proposed technique compared with that by CS technique. Thus a more precise reconstruction can be obtained.



(a) 35.16 (1%, *PZWS*) (b) 30.31(10%, *PZWS*) (c) 22.14(30%, *PZWS*)



(d) 33.14(1%, *MSST*) (e) 32.95(10%, *MSST*) (f) 31.94(30%, *MSST*)

Fig.3. Reconstructed Images versus different packet loss rate

Simulations 2 is taken over Fig.2(a) to demonstrate the capability of the proposed communication scheme to handle data erasure caused by communication interrupt. Traditional communication scheme using packetizable zerotree wavelet [11](called *PZWS*) is considered for comparison. For fair comparison, the similar packetization scheme is applied to the *MSST* bit-streams. Fig.3 lists the visual results versus variant packet erasure with β be 0.5*bpp*. As displayed in Fig.3, *PZWS* achieves an outstanding reconstruction quality at a low packet loss rate, but the superiority decreases even disappears with increased packet loss rate. When the packet loss rate is 30%, some regions are blurred so heavily that we can't distinguish the objects of image. While when the packet loss rate increases from 1% to 30%, the images obtained by *MSST* are barely changed in both the visual aspect and their PSNRs. The same conclusion is verified by the PSNR curves versus variant packet erasure in Fig.4, where β is fixed as 0.2*bpp* and1.0*bpp*, respectively. During the whole range of packet erasure, curves of the *PZWS* descend sharply and the result is considered to be unacceptable under 30% packet erasure, while that of *MSST* decreased relatively stable. Fig.5 also present the PSNR curves versus varied bit budget with packet loss rate fixed 10% and 20%. As figures indicated, PSNR values of the *MSST* are superior to that of the *PZWS* for the same packet loss rate, which further demonstrate the proposed *MSST* is more robustness for the packet erasure and can provide a more stable communication.

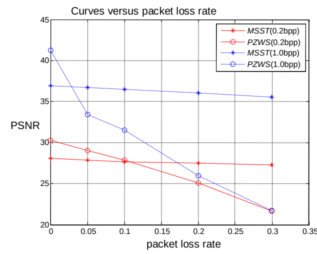


Fig.4 PSNR versus packet loss rate

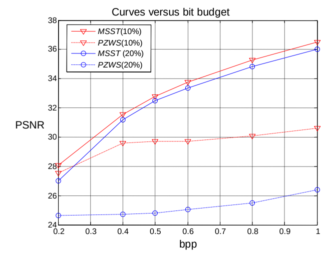


Fig.5 PSNRversus bit budget

V.Conclusion

In this letter, we have proposed a low-complex *MSST* scheme based on CS for near space communication. Our scheme exploits the correlation CS measurements and a scalable CS-based coding increasing coding efficiency has been developed. Using the *democracy* and scalability of the CS, our scheme achieves a reliable communication over data erasure.

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