Empirical Risk Minimization Based Analysis of Segmented Compressed Sampling

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Abstract—A new segmented compressed sampling (CS) method has been proposed in our earlier publication. The essence of this method is to collect a larger number of samples (although correlated) than the number of parallel branches of mixers and integrators in the analog-to-information converter. The objective of this paper is to show that the additional samples obtained based on the proposed segmented CS method help to improve the quality of signal recovery in terms of mean squared error. The proof is given for the empirical risk minimization recovery method, which includes as special case the well-known least absolute shrinkage and selection operator algorithm.

I. INTRODUCTION AND NOTATIONS

The compressed sampling (CS) enables us to recover sparse or compressible signals from fewer samples than the possible number of projections in the signal representation [1]–[3]. It has applications in such fields as cognitive radio [4], channel estimation [5], etc. Let \( f \) be an \( N \times 1 \) discrete-time sparse signal represented in an arbitrary sparsity basis \( \Psi \) as

\[
f = \Psi^H x
\]

where \( (\cdot)^H \) stands for Hermitian transpose. We say that \( f \) is sparse if its representation in \( \Psi \), \( x \) has only a small number of non-zero coefficients.

According to the conventional CS process an analog signal is first sampled at the Nyquist rate and then the samples are obtained from a random matrix \( \Phi \) called measurement matrix with its original waveforms in the set of sub-samples instead of a single sample in each BMI. As a result, the following \( K \times M \) matrix of sub-samples can be obtained

\[
Y = \begin{pmatrix}
y_{1,1} & y_{1,2} & \cdots & y_{1,M} \\
y_{2,1} & y_{2,2} & \cdots & y_{2,M} \\
\vdots & \vdots & \ddots & \vdots \\
y_{K,1} & y_{K,2} & \cdots & y_{K,M}
\end{pmatrix}
\]

where \( y_{i,j} \) is the \( j \)-th sub-sample measured against the sampling waveform of the \( i \)-th BMI. The elements of \( Y \) are used to obtain \( K \) original samples as \( y_k = \sum_{m=1}^{M} y_{k,m}, \ k = 1, \ldots, K \) as well as \( K_a \) additional samples. The \((K + 1)\)-st sample can be obtained as a summation of the \( M \) sub-samples on the main diagonal of \( Y \). The \((K + 2)\)-nd sample is composed of the \( M \) sub-samples on the second diagonal, and so on. Such scheme of collecting additional samples is shown in Fig. 2 for the case \( K_a = K \), and it has been further generalized in [7].

Our segmented CS method is equivalent to extending the original measurement matrix \( \Phi \) by adding to it \( K_a \) additional sampling waveforms composed of the parts of the original waveforms in \( \Phi \). Particularly, let \( \Phi \) be the original \( K \times N \) measurement matrix with its \( k \)-th row being \( \phi_k = (\phi_{k,1}, \ldots, \phi_{k,M}) \) where \( \phi_{k,i}, \ i = 1, \ldots, M \) are some

![Fig. 1. The structure of the AIC based on RMPI.](image-url)
vectors. For simplicity, the length of $\phi_i$ is considered to be an integer number equal to $N/M$. Then the $K \times N$ extended measurement matrix corresponding to the case in Fig. 2 is

$$
\Phi_e = \begin{pmatrix} 
\phi_{1,1} & \phi_{1,2} & \cdots & \phi_{1,M} \\
\vdots & \vdots & \ddots & \vdots \\
\phi_{K,1} & \phi_{K,2} & \cdots & \phi_{K,M} \\
\phi_{\pi_1(K),1} & \phi_{\pi_1(K),2} & \cdots & \phi_{\pi_1(K),M} \\
\phi_{\pi_2(K),1} & \phi_{\pi_2(K),2} & \cdots & \phi_{\pi_2(K),M} \\
\end{pmatrix}
$$

(3)

where $\Phi_1$ is composed of the last $K_e$ rows of $\Phi_e$, $K_e \triangleq K + K_a$, and $\pi_k(k) = ((s + k - 2) \mod K) + 1, s, k = 1, \ldots, K$ are the permutations applied to different columns of $\Phi$.

### III. AVERAGE ANALYSIS OF THE RECOVERY QUALITY

Let the entries of the original measurement matrix $\Phi$ be selected with equal probability as $\pm 1/\sqrt{N}$. This corresponds to Bernoulli distribution with variance $1/N$. The risk $r(\hat{f})$ of a candidate reconstruction $\hat{f}$ and its empirical risk $\hat{r}(\hat{f})$ are defined as

$$
r(\hat{f}) \triangleq \frac{\|\hat{f} - f\|^2}{N} + \sigma^2, \quad \hat{r}(\hat{f}) \triangleq \frac{1}{K} \sum_{j=1}^{K} (y_j - \phi_j \hat{f})^2.
$$

(4)

Then the empirical risk minimization based recovery is equivalent to solving the following optimization problem [3]

$$
\hat{f}_K = \arg \min_{f \in F(B)} \left\{ \hat{r}(f) + \frac{c(\hat{f}) \log 2}{\epsilon K} \right\}
$$

(5)

where $F(B) \triangleq \{ f : \|f\|^2 \leq NB^2 \}$, $B$ is the average energy bound on each entry of $f$, $c(\hat{f})$ is a nonnegative number assigned to a candidate signal $f$, and $\epsilon = 1/(50(B + \sigma^2))$.

For our segmented CS method, the main difficulty of the recovery quality analysis based on the empirical risk minimization method is the fact that the additional samples are correlated with the original samples.

The “excess risk” between the candidate reconstruction $\hat{f}$ of the signal sampled using the extended measurement matrix $\Phi_e$ and the actual signal $f$ is $r(\hat{f}, f) \triangleq r(\hat{f}) - r(f)$.

Similar, the “empirical excess risk” between the candidate signal reconstruction and the actual signal is defined as

$$
r(\hat{f}, f) \triangleq \hat{r}(\hat{f}) - \hat{r}(f).
$$

The difference between the “excess risk” and the “empirical excess risk” can be found as

$$
r(\hat{f}, f) - \hat{r}(f) = \frac{1}{K_e} \sum_{j=1}^{K_e} (U_j - E[U_j])
$$

(6)

where $U_j \triangleq (y_j - \phi_j \hat{f})^2 - (y_j - \phi_j f)^2$. The mean squared error (MSE) between the candidate reconstruction and the actual signal can be expressed as

$$
\text{MSE} \triangleq E \{ \|g\|^2 \} = Nr(\hat{f}, f)
$$

(7)

where $g \triangleq \hat{f} - f$. Let $U$ be an upper bound for the right-hand side of (6). The MSE in (7) is consequently upper bounded by $N \text{r}(\hat{f}, f) +NU$. Typically, the Craig-Bernstein inequality [8] is utilized to find the upper bound $U$. This inequality states that the probability of the following event

$$
1 - \frac{K_e}{K} \sum_{j=1}^{K_e} (U_j - E[U_j]) \leq \frac{\log \left( \frac{2}{\delta} \right)}{K_e} + \frac{\epsilon \var{\sum_{j=1}^{K_e} U_j}}{2K_e(1 - \zeta)}
$$

(8)

is greater than or equal to $1 - \delta$ for $0 < \epsilon \leq \zeta < 1$, if the random variables $U_j$ satisfy the following moment condition for some $h > 0$ and all $k \geq 2$

$$
E \{ |U_j - E[U_j]|^h \} \leq \frac{k! \var{U_j} h^{k-2}}{2}.
$$

(9)

The second term in the right-hand side of (8) contains the variance $\var{\sum_{j=1}^{K_e} U_j}$ for which we now need to find an upper bound.

In the case of the extended measurement matrix, the random variables $U_j, j = 1, \ldots, K_e$ satisfy the moment condition for the Craig-Bernstein inequality with the same coefficient $h = 16B^2e + 8\sqrt{2}B\sigma$, where $\sigma^2$ is the variance of the Gaussian noise [3]. Moreover, it is easy to show that the following bound on the variance of $U_j$ is valid for the extended measurement matrix

$$
\var{U_j} \leq 2 \frac{\|g\|^2}{2N} + \frac{\|g\|^2}{N} \leq (8B^2 + 4\sigma^2) r(\hat{f}, f).
$$

(10)

However, unlike [3], in the case of the extended measurement matrix, the variables $U_j$ are not independent from each other. Thus, we can not simply replace the term $\var{\sum_{j=1}^{K_e} U_j}$ with the sum of the variances. Using the definition of the variance, we can write that

$$
\var{\sum_{j=1}^{K_e} U_j} \triangleq E \left\{ \left( \sum_{j=1}^{K_e} U_j \right)^2 \right\} - \left( E \{ \sum_{j=1}^{K_e} U_j \} \right)^2
$$

$$
= \sum_{j=1}^{K_e} (E[U_j]^2) + 2 \sum_{j=1}^{K_e-1} \sum_{j=1}^{K_e} E[U_j U_j] - K_e^2 \left( \frac{\|g\|^2}{N} \right)^2
$$

$$
= K_e \left( E[U_j^2] - \frac{\|g\|^2}{N} \right)^2
$$
\[ + 2 \frac{K_r}{R} \sum_{i=1}^{R} \sum_{j=1}^{K_r} \left( E[U_iU_j] - \frac{\|g\|^2}{N} \right)^2 \]
\[ = \sum_{j=1}^{K_r} \text{var}(U_j) + 2 \frac{K_r}{R} \sum_{j=1}^{K_r} \sum_{i=1}^{R} \left( E[U_iU_j] - \frac{\|g\|^2}{N} \right)^2 \]
where the upper bound on \( \text{var}(U_j) \) is given by (10). Using the fact that the random noise components \( w_i \) and \( w_j \) are independent from \( \phi_i g \) and \( \phi_j g \) (see the noisy model (1)), respectively, \( E[U_iU_j] \) can be expressed as
\[ E[U_iU_j] = E[(w_i, \phi_j g - (\phi_i g))^2 | (w_j, \phi_j g - (\phi_j g))^2] = 4E[w_i w_j]E[\phi_i g \phi_j g] - 2E[w_i]E[\phi_i g \phi_j g] - 2E[w_j]E[\phi_i g \phi_j g] + E[(\phi_i g)^2(\phi_j g)^2]. \]
The latter expression can be further simplified using the fact that \( E[w_i] = E[w_j] = 0 \). Thus, we obtain that
\[ E[U_iU_j] = 4E[w_i w_j]E[(\phi_i g)(\phi_j g)] + E[(\phi_i g)^2(\phi_j g)^2]. \]
(13)
It is easy to verify that if \( \phi_i \) and \( \phi_j \) are independent, then \( E[U_iU_j] = E[(\phi_i g)^2]E[(\phi_j g)^2] = (\|g\|^2/N)^2 \) which indeed coincides with [3]. However, in our case, if \( \phi_i \) and \( \phi_j \) indeed depend on each other, they have \( L = N/M \) common entries, while the rest of the entries are independent. In addition, the additive noise terms \( w_i \) and \( w_j \) are no longer independent random variables and, thus, \( E[w_i w_j] = \sigma^2/M \).
Without loss of generality, let the first \( L \) entries of \( \phi_i \) and \( \phi_j \) be the same, that is,
\[ \phi_i,g = g_1 a_1 + \ldots + g_L a_L + g_{L+1} \phi_i L+1 + \ldots + g_N \phi_i N \]
\[ \phi_j,g = g_1 a_1 + \ldots + g_L a_L + g_{L+1} \phi_j L+1 + \ldots + g_N \phi_j N \]
with \( a_1, \ldots, a_L \) being the common part between \( \phi_i \) and \( \phi_j \). Let \( g_i \) be a sub-vector of \( g \) containing the \( L \) elements of \( g \) corresponding to the common part between \( \phi_i \) and \( \phi_j \), and \( g_{A,i} \) be the sub-vector comprising the rest of the elements. Then using the fact that \( A, P_i, \) and \( P_j \) are all zero mean independent random variables, we can express \( E[(\phi_i g)(\phi_j g)] \) from the first term on the right-hand side of (13) as
\[ E[(\phi_i g)(\phi_j g)] = E[(A + P_i)(A + P_j)] = E[A^2] + E[AP_i] + E[AP_j] + E[P_i P_j] \]
\[ = E[A^2] = \frac{\left( \sum_{k=1}^{L} \frac{g_k^2}{N} \right)^2}{N}. \]
(14)
Using the facts that \( 4E[w_i w_j] = 4\sigma^2/M, E[A^2] = \|g\|^2/N, \) and \( E[P_i^2] = \|g\|^2/N \), (17) can be further rewritten as
\[ E[(\phi_i g)^2(\phi_j g)^2] = E[A^4 + A^2 P_i^2 + A^2 P_j^2 + P_i^2 P_j^2] \]
\[ = E[A^4] + 2\frac{\|g\|^2}{N} \frac{\|g\|^2}{N} + \frac{\|g\|^2}{N} \frac{\|g\|^2}{N} \]
\[ = E[A^4] + \left( \frac{\|g\|^2}{N} \right)^2 - \left( \frac{\|g\|^2}{N} \right)^2. \]
(18)
Substituting (16) and (18) into (13), we obtain that
\[ E[U_iU_j] = \frac{4\sigma^2}{M} \frac{\|g\|^2}{N} + E[A^4] + \left( \frac{\|g\|^2}{N} \right)^2 - \left( \frac{\|g\|^2}{N} \right)^2. \]
(19)
Moreover, substituting (19) into (11), we find that
\[ \text{var} \left\{ \sum_{j=1}^{K_r} U_j \right\} = \sum_{j=1}^{K_r} \text{var}(U_j) \]
\[ + 2 \sum_{\phi_i, \phi_j, \text{dependent}} \left( E[A^4] - \left( \frac{\|g\|^2}{N} \right)^2 + \frac{4\sigma^2}{M} \frac{\|g\|^2}{N} \right). \]
(20)
Using the fact that the extended measurement matrix is constructed so that the waveforms \( \phi_i, i = K + 1, \ldots, K_e \) are built upon \( M \) rows of the original matrix and also using the inequality \( E[A^4] - \left( \frac{\|g\|^2}{N} \right)^2 \leq 2 \left( \frac{\|g\|^2}{N} \right)^2 \) for all these \( M \) rows (see, for example, [3]), we obtain for every \( \phi_i, i = K + 1, \ldots, K_e \) that
\[ \sum_{k=1}^{M} \left( E[A^4] - \left( \frac{\|g\|^2}{N} \right)^2 + \frac{4\sigma^2}{M} \frac{\|g\|^2}{N} \right) \]
\[ \leq \sum_{k=1}^{M} \left( 2 \left( \frac{\|g\|^2}{N} \right)^2 + \frac{4\sigma^2}{M} \frac{\|g\|^2}{N} \right). \]
(21)
where \( g_k \) corresponds to the first \( L \) entries of \( g \) for \( k = 1 \), to the entries from \( L + 1 \) to \( 2L \) for \( k = 2 \) and so on. Applying also the triangle inequality, we find that
\[ \sum_{k=1}^{M} \left( 2 \left( \frac{\|g\|^2}{N} \right)^2 + \frac{4\sigma^2}{M} \frac{\|g\|^2}{N} \right) \]
\[ \leq 2 \left( \frac{\|g\|^2}{N} \right)^2 + \frac{4\sigma^2}{M} \frac{\|g\|^2}{N}. \]
(22)
Combining (21) and (22) and using the fact that there are \( K_a \) additional rows in the extended measurement matrix, we obtain that
\[ 2 \sum_{\phi_i, \phi_j, \text{dependent}} \left( E[A^4] - \left( \frac{\|g\|^2}{N} \right)^2 + \frac{4\sigma^2}{M} \frac{\|g\|^2}{N} \right) \]
\[ \leq 4K_a \left( \frac{\|g\|^2}{N} \right)^2 + \frac{8\sigma^2K_a}{M} \frac{\|g\|^2}{N}. \]
(23)
Noticing that \(\|g\|^2/N = r(\hat{f}, f)\) and \(\|g\|^2 \leq 4NB^2\), the right-hand side of (23) can be upper bounded as

\[
4K_a \left( \frac{\|g\|^2}{N} \right)^2 + \frac{8\sigma^2 K_a}{M} \cdot \frac{\|g\|^2}{N} \leq 16K_aB^2 r(\hat{f}, f) + \frac{8\sigma^2 K_a}{M} r(\hat{f}, f)
\]  
(24)

Using the upper bound (24) for the second term in (20) and the upper bound (10) for the first term in (20), we finally can upper bound the variance \(\sum_{j=1}^{K_a} U_j\) as

\[
\text{var} \left\{ \sum_{j=1}^{K_a} U_j \right\} \leq K_a \left( 8B^2 \left( 1 + \frac{2K_a}{K_e} \right) + 4\sigma^2 \left( 1 + \frac{2K_a}{MK_e} \right) \right) r(\hat{f}, f). \]  
(25)

Thus, based on the Craig-Bernstein inequality, the probability that for a given candidate reconstruction \(\hat{f}\) the following inequality holds

\[
r(\hat{f}, f) - \hat{r}(\hat{f}, f) \leq \frac{\log(\frac{1}{\delta})}{K_e} + \frac{8B^2 \left( 1 + \frac{2K_a}{K_e} \right) + 4\sigma^2 \left( 1 + \frac{2K_a}{MK_e} \right) }{2(1-\zeta)} r(\hat{f}, f) \epsilon
\]  
(26)

is greater than or equal to \(1-\delta\).

Let \(c(\hat{f})\) be chosen such that \(\sum_{f \in \mathcal{F}(B)} 2^{c(f)} \leq 1\), i.e., the Kraft inequality is satisfied (see also [3]), and let \(\delta(\hat{f}) = 2^{-c(\hat{f})/\delta}\). Applying the union bound to (26), it can be shown that for all \(\hat{f} \in \mathcal{F}(B)\) and for all \(\delta > 0\), the following inequality holds with probability of at least \(1-\delta\)

\[
r(\hat{f}, f) - \hat{r}(\hat{f}, f) \leq \frac{c(\hat{f}) \log 2 + \log(\frac{1}{\delta})}{K_e} + \frac{8B^2 \left( 1 + \frac{2K_a}{K_e} \right) + 4\sigma^2 \left( 1 + \frac{2K_a}{MK_e} \right) }{2(1-\zeta)} r(\hat{f}, f) \epsilon
\]  
(27)

Finally, setting \(\zeta = \epsilon h\) and

\[
\epsilon < \frac{1}{\left( 4 + 2K_a + 16\epsilon \right) B^2 + 8\sqrt{B}\sigma + 2\sigma^2 \left( 1 + \frac{2K_a}{MK_e} \right) ^2}
\]  
(28)

where \(0 < \epsilon h \leq \zeta < 1\) as required by the Craig-Bernstein inequality, the following inequality holds with probability of at least \(1-\delta\) for all \(\hat{f} \in \mathcal{F}(B)\)

\[
(1-a)r(\hat{f}, f) \leq \hat{r}(\hat{f}, f) + \frac{c(\hat{f}) \log 2 + \log(\frac{1}{\delta})}{K_e} \epsilon.
\]  
(29)

The following result on the recovery performance of the empirical risk minimization method is in order.

**Theorem 1.** Let \(\epsilon\) be chosen as

\[
\epsilon = \frac{1}{(60(B + \sigma)^2)}
\]  
(31)

which satisfies the inequality (29), then the signal reconstruction \(\hat{f}_{K_e}\) given by

\[
\hat{f}_{K_e} = \arg \min_{\hat{f} \in \mathcal{F}(B)} \left\{ \hat{r}(\hat{f}) + \frac{c(\hat{f}) \log 2}{K_e} \right\}
\]  
(32)

satisfies the inequality

\[
E \left\{ \frac{\|\hat{f}_{K_e} - f\|^2}{N} \right\} \leq C_{1e} \min_{\hat{f} \in \mathcal{F}(B)} \left\{ \frac{\|\hat{f} - f\|^2}{N} + \frac{c(\hat{f}) \log 2 + 4}{K_e} \right\}
\]  
(33)

where \(C_{1e}\) is the constant given as

\[
C_{1e} = \frac{1}{1-a} = \frac{2 \left(1 + \frac{2K_a}{K_e} \right) \left( \frac{B}{\sigma} \right)^2 + \left(1 + \frac{2K_a}{MK_e} \right)^2}{(30-8e) \left( \frac{B}{\sigma} \right)^2 + (60-4\sqrt{2}) \left( \frac{B}{\sigma} \right)^2 + 30}
\]  
(34)

with a obtained from (28) for the specific choice of \(\epsilon\) in (31).

The following result on the achievable recovery performance for a sparse or compressible signal sampled based on the extended measurement matrix \(\Phi_e\) is also of interest.

**Theorem 2.** For a sparse signal \(f \in \mathcal{F}_s(B,S) \triangleq \{ f : \|f\|^2 \leq NB^2, \|f\|_0 \leq S \}\) of sparsity level \(S\) and the reconstructed signal \(\hat{f}_{K_e}\) obtained according to (32) with \(\epsilon\) as in (31), there exists a constant \(C_{2e} = C_{2e}(B,\sigma) > 0\), such that

\[
\sup_{f \in \mathcal{F}(B,S)} E \left\{ \frac{\|\hat{f}_{K_e} - f\|^2}{N} \right\} \leq C_{1e}C_{2e} \left( \frac{K_e}{S \log N} \right)^{-1}
\]  
(35)

where \(C_{1e}\) is the constant given by (34).

Similar for a compressible signal \(f \in \mathcal{F}_c(B,\alpha,C_A) \triangleq \{ f : \|f\|^2 \leq NB^2, \|f\|_{(m)} \leq NC_A^{-m-2a} \}\) and corresponding reconstructed signal \(\hat{f}_{K_e}\) obtained as in the previous case, there exists a constant \(C_{2e} = C_{2e}(B,\sigma,C_A) > 0\), such that

\[
\sup_{f \in \mathcal{F}(B,\alpha,C_A)} E \left\{ \frac{\|\hat{f}_{K_e} - f\|^2}{N} \right\} \leq C_{1e}C_{2e} \left( \frac{K_e}{\log N} \right)^{-2a + \alpha}
\]  
(36)

where \(\hat{f}_{(m)}\) is the best \(m\)-term approximation of \(f\) which is obtained by retaining the \(m\) most significant coefficients of \(\text{vector} \ x\).
quality, i.e., the corresponding mean MSE for the case of $\Phi_c$ is expected to be better than that of the case of $\Phi$.

The results given in this paper are for the case $K_a \leq K$. However, the segmented CS method can be easily generalized to the case with $K_a > K$. Such a generalization is carried out in [7] where general forms of Theorems 1 and 2 are also given.

IV. SIMULATION RESULTS

A time sparse signal of dimension of 128 with only 3 randomly chosen non-zero entries is used. Three different measurement matrices are compared (i) the original $K \times N$ measurement matrix; (ii) the extended measurement matrix corresponding to the segmented CS method; and (iii) the enlarged measurement matrix with i.i.d. entries and of the same size as the extended matrix. The number of segments $M$ is 8 and the number of original measurements is $K = 24$.

The minimization problem (5) is solved to obtain a candidate reconstruction $\hat{f}_{K'}$ of the original sparse signal $f$. Considering $\hat{f}_{K'} = \Psi^H \hat{x}_{K'}$, (5) can be rewritten in terms of $\hat{x}_{K'}$ as

$$\hat{x}_{K'} = \arg \min_{\hat{x}} \left\{ \tilde{r}(\Psi^H \hat{x}) + \frac{c(\hat{x}) \log 2}{\epsilon K'} \right\}$$

and solved using the iterative bound optimization procedure [3]. This procedure uses the threshold $\sqrt{2 \log 2 \log N / \lambda \epsilon}$ where $\lambda$ is the largest eigenvalue of the matrix $\Phi^H \Phi$. In our simulations, this threshold is set to 0.035 for the case of the extended measurement matrix and 0.05 for the cases of the original and enlarged measurement matrices. These threshold values are optimized as recommended in [3]. The stopping criterion for the iterative bound optimization procedure is $\|\hat{x}^{(i+1)} - \hat{x}^{(i)}\|_\infty \leq \theta$ where $\|\cdot\|_\infty$ is the $l_\infty$ norm and $\hat{x}^{(i)}$ denotes the value of $\hat{x}$ obtained in $i$-th iteration. The value $\theta = 0.001$ is selected.

Fig. 4 shows the MSEs for all three measurement matrices versus the ratio $K_a / K$ for three different values of SNR of 5, 15 and 25 dB when the entries of the original and the enlarged measurement matrices are i.i.d. zero-mean Bernoulli distributed random variables with variance $1/N$. It can be seen that the recovery quality is indeed improved when the extended measurement matrix is used instead of the original measurement matrix.

V. CONCLUSIONS

It has been shown that the segmented CS method for AIC provides better average signal recovery performance than the conventional AIC. Analytical results on MSE, which prove the superiority of the segmented CS method, have been obtained. Simulation results confirm the improvements archived in signal recovery for our segmented CS.

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