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Research paper

Improved Correlation Coefficient Sparsity Adaptive Matching Pursuit in Noisy Condition

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Abstract

Background and Objectives: In the realm of compressed sensing, most greedy sparse recovery algorithms necessitate former information about the signal's sparsity level, which may not be available in practical conditions. To address this, methods based on the Sparsity Adaptive Matching Pursuit (SAMP) algorithm have been developed to self-determine this parameter and recover the signal using only the sampling matrix and measurements. Determining a suitable Initial Value for the algorithm can greatly affect the performance of the algorithm.
Methods: One of the latest sparsity adaptive methods is Correlation Calculation SAMP (CCSAMP), which relies on correlation calculations between the signals recovered from the support set and the candidate set. In this paper, we present a modified version of CCSAMP that incorporates a pre-estimation phase for determining the initial value of the sparsity level, as well as a modified acceptance criteria considering the variance of noise.
Results: To validate the efficiency of the proposed algorithm over the previous approaches, random sparse test signals with various sparsity levels were generated, sampled at the compression ratio of 50%, and recovered with the proposed and previous methods. The results indicate that the suggested method needs, on average, 5 to 6 fewer iterations compared to the previous methods, just due to the pre-estimation of the initial guess for the sparsity level. Furthermore, as far as the least square technique is integrated in some parts of the algorithm, in presence of noise the modified acceptance criteria significantly improve the success rate while achieving a lower mean squared error (MSE) in the recovery process.
Conclusion: The pre-estimation process makes it possible to recover signal with fewer iterations while keeping the recovery quality as before. The fewer the number of iterations, the faster the algorithm. By incorporating the noise variance into the accept criteria, the method achieves a higher success rate and a lower mean squared error (MSE) in the recovery process.

Introduction

Recently, there has been a growing focus among researchers on sub-Nyquist sampling methods, due to their application in numerous industrial products, such as image encryption, radars, mm-wave body scanners and pocket handheld ultrasound scanners.

These applications almost utilize the wideband signals, which when sampled at their traditional Nyquist rate, a vast number of samples would be generated, leading to significant challenges related to processing and storage. Sub-Nyquist sampling methods, such as modulated wideband converter (MWC), offer solutions to overcome these issues by reducing the sampling rate down to the Landau rate [1]-[5].

The key concept behind these techniques is compressed sensing [6], in which data is captured in a compressed format. The three main stages of compressed sensing are sparsification, compressed sampling, and recovery. Sparsification transforms the original signal into a sparse format. Compression involves taking measurements by multiplying the sparse signal by a sensing matrix that has specific characteristics. Finally, in the recovery phase, the signal is reconstructed from the measurements employing the sparse recovery algorithms.

These algorithms can be divided into three primary categories [7]. The first group includes methods based on convex relaxation, such as BP (Basis Pursuit) and LASSO, which attempt to find the solution by shaping linear programming (LP) problems [8], [9]. Although these methods are considered accurate, regarding their high computational complexity, they might not be applicable to practical real large-scale problems.

The second group consists of non-convex methods that rely on statistical approaches, such as BCS (Bayesian compressed sensing) [10].

The third group comprises greedy algorithms that implement the recovery process through iterative steps [4]. It should be noted that these algorithms are the most popular practical techniques because of their lower implementation complexity. Among these, Matching Pursuit (MP) algorithms are the most widely used and practical, known for their performance. In each iteration of the simple OMP, the column of the sensing matrix related to the highest correlation value with the samples is selected. This atom selection process is irreversible, and there is no chance to correct for incorrectly selected atoms [11], [12].

Other algorithms, such as CoSaMP and IHT, incorporate a backtracking approach that means in addition to selecting a certain number of atoms, they are capable of removing excessively selected ones by applying a threshold in each iteration [13]-[16]. However, these greedy algorithms need former knowledge about the signal's sparsity level, which may not always be available in practical situations.

To address this, a sub-category of greedy algorithms, known as Sparsity Adaptive Matching Pursuit (SAMP), has been developed to estimate the sparsity level as well as the recovered signal [17]-[19].

These methods start with an initial value of the sparsity level and gradually adjust it in each iteration with a specific step size. Various versions of SAMP have been developed to enhance performance in both speed and accuracy. The fixed step size is used in the basic SAMP [13], while in FSAMP, the step size increases linearly [20]. In SAMPVSS and IGSAMP, exponential functions are offered to increase the step size [21]-[24]. In Some recent algorithm, such as CCSAMP, the step size is adjusted based on the correlation coefficient calculated in each iteration [25], [26]. It is notable that the initial value selection for the step size significantly impacts the algorithm's performance. The small step size will increase the number of iterations, while the big value might lead to the overestimation of the sparsity level.

The main contribution of this work is the integration of a pre-estimation phase to determine the optimal initial step size for CCSAMP, leading to a reduced number of required iterations. Additionally, we have established a different termination criterion, significantly increasing the success rate of CCSAMP under noisy conditions.

This article is organized as follows: the second section provides an overview of the compressed sensing and SAMP algorithms. The third section introduces the pre-estimation phase and the new termination criteria. The implementation results, validating the performance of the presented work, are presented in the fourth section.

Overview of Compressed Sensing and SAMP

Consider a signal $\mathbf{\theta}\epsilon\mathbb{R}^{N\times1}$ with length of N which is targeted to be compressed to a measurement signal $\mathbf{y}\epsilon\mathbb{R}^{M\times1}$ with length of M, where M is far smaller than N ($M << N$). But as far as compressed sensing concepts are only applicable to the either sparse or compressible signals, as shown in below equation, in case of having a non-sparse original signal, $\mathbf{\theta}$ should be represented in terms of the sparse basis of $\boldsymbol{\Psi}$ and the sparse signal $\mathbf{x}\epsilon\mathbb{R}^{N\times1}$, such that $\mathbf{x}$ contain only K non-zero elements.

$$\mathbf{\theta} = \boldsymbol{\Psi}\,\mathbf{x} \tag{1}$$

In different cases, matrix $\boldsymbol{\Psi}$ may vary. Depending on the type of application, it can be constructed utilizing Fourier transform, Discrete Cosine Transform (DCT), Wavelet transform, or other similar transforms. After a sparse representation of the signal, the compressed measurement $\mathbf{y}_{M\times1}$ is calculated by multiplying the matrix $\boldsymbol{\Phi}_{M\times N}$ that decreases the dimension from N to M, as shown below:

$$\mathbf{y} = \boldsymbol{\Phi}\,\boldsymbol{\theta} = \boldsymbol{\Phi}\boldsymbol{\Psi}\,\mathbf{x} = \boldsymbol{A}\mathbf{x} \tag{2}$$

where $\boldsymbol{A} = \boldsymbol{\Phi}\boldsymbol{\Psi}$. It is noted that $\boldsymbol{A}$ is named the sensing matrix throughout this article, and to guarantee a successful recovery process of the original signal from the measurements, this matrix must satisfy special characteristics, specifically the Restricted Isometry Property (RIP). This condition is met only if the below equation is satisfied with constant $\delta_k \in (0,1)$ [27].

$$(1-\delta_k)\|\mathbf{x}\|_2^2 \le \|\boldsymbol{A}\mathbf{x}\|_2^2 \le (1+\delta_k)\|\mathbf{x}\|_2^2 \tag{3}$$

One method of recovering the original signal from the samples $\mathbf{y}$ is solving the l_0-norm minimization problem, as show in (4). The goal is to find the sparsest signal that, when sampled with $\boldsymbol{A}$, it produces the samples $\mathbf{y}$.

$$\hat{\mathbf{x}} = \arg\min \|\mathbf{x}\|_0 \quad s.t. \mathbf{y} = \boldsymbol{A}\mathbf{x} \tag{4}$$

In this formula $\| \ \|_0$ denotes the l_0 −norm and reflects the signal's sparsity level. However, this method is an NP-hard problem, and its complexity increases significantly as the dimension grows. So, it is recommended to approximate it with a l_1-norm minimization problem, as shown below [28].

$$\hat{\mathbf{x}} = \arg\min \|\mathbf{x}\|_1 \quad s.t. \mathbf{y} = \boldsymbol{A}\mathbf{x} \tag{5}$$

Although this method can recover the signal with high accuracy, greedy algorithms are often preferred due to their advantage of lower implementation complexity. Among these, certain algorithms, based on the SAMP algorithm, do not require any former information about the signal's sparsity level. The pseudo-code related to the basic SAMP is presented in Algorithm 1.

Algorithm 1: Sparsity Adaptive Matching Pursuit (SAMP)

Input params: measurement signal $\mathbf{y}$, sensing matrix $\boldsymbol{A}$, initial step-size s_0
Output: recovered signal $\hat{\mathbf{x}}$
Initial: $\hat{\mathbf{x}} = 0$; $\mathbf{r}_0 = \mathbf{y}$; $F_0 = \emptyset; L = s_0; t = 1;$
while $(true)$
$B_t = \max(\boldsymbol{A}^H \mathbf{r}_{t-1}, L)$
$C_t = F_{t-1} \cup B_t$
$F = \max(\boldsymbol{A}_{C_t}^{\dagger}\mathbf{y}, L)$
$\mathbf{r} = \mathbf{y} - \boldsymbol{A}_F \boldsymbol{A}_F^{\dagger}\mathbf{y}$
if $\|\mathbf{r}\|_2 < \varepsilon$
  break;
else if $\|\mathbf{r}\|_2 \geq \|\mathbf{r}_{t-1}\|_2$
  $L = L + s_0$
else
  $F_t = F; \mathbf{r}_t = \mathbf{r}; t = t + 1;$
end
$\hat{\mathbf{x}} = \boldsymbol{A}_F^{\dagger}\mathbf{y}$
end while

In each iteration, firstly, the candidate set C_t is calculated by finding the L indices corresponding to the largest correlation between columns of the sensing matrix $\boldsymbol{A}$ and the previous residual signal. The function $\max(\mathbf{temp}, L)$ returns the index set associated with the L highest value of the input vector of temp. Then, the signal is temporarily recovered related to the union set of F_{t-1} and C_t. Then, as the backtracking stage, the final index set is created by selecting its L largest value.

Based on this set of indices, the residual $\mathbf{r}$ is updated. During each iteration. If the correct atoms are selected, the norm of $\mathbf{r}$ tends to decrease.

Otherwise, it indicates that the chosen sparsity level L is insufficient and must be increased by the step size s_0. The repetition of the algorithm continues until the norm of $\mathbf{r}$ becomes smaller than a predefined epsilon. Meanwhile, the algorithm might stop unsuccessfully if L exceeds M or if the iteration counter t exceeds the maximum number of iterations.

As far as the SAMP algorithm uses a fixed step size s, it is prone to either overestimate or underestimate the correct sparsity level. In different modifications of the SAMP algorithm, others have made attempts to make the step size variable.

For instance, in the CCSAMP method, a varying step size is introduced that adjusts based on the correlation between $\mathbf{y}_{C_t}$ and $\mathbf{y}_F$ obtained through the Least Squares technique for the candidate set and the final set, as illustrated in (6) [25]. Step size adjustment is achieved through a multilevel decision-making process. Low correlation indicates a significant change in each iteration. So, the step size must grow. In other words, the lower the correlation, the higher the step size. As the correlation converges to 1, the step size must be selected more cautiously with small values.

$$\begin{aligned}
&\mathbf{y}_{C_t} = \boldsymbol{A}_{C_t}(\boldsymbol{A}_{C_t}{}^{\boldsymbol{T}}\boldsymbol{A}_{C_t})^{-\mathbf{1}}\boldsymbol{A}_{C_t}{}^{\boldsymbol{T}}\ \mathbf{y} \\
&\mathbf{y}_F = \boldsymbol{A}_F(\boldsymbol{A}_F{}^{\boldsymbol{T}}\boldsymbol{A}_F)^{-\mathbf{1}}\boldsymbol{A}_F{}^{\boldsymbol{T}}\ \mathbf{y} \\
&\rho_t = corr(\mathbf{y}_{C_t}, \mathbf{y}_F) \\
&s = \begin{cases} s_0 + 10 * (1 - \rho_t) & \rho_t < 0.9 \\ s_0 & \rho_t < 1 - 10^{-6} \\ 1 & otherwise \end{cases}
\end{aligned} \tag{6}$$

The Proposed Method

A. Pre-estimation Phase

The performance of CCSAMP slightly varies with different initial values of the sparsity level. This section discusses the details of ICCSAMP, specifically how the initial sparsity level is calculated through a pre-estimation phase by implementing a matching test [21], [29].

To estimate the initial sparsity level, the index set S_0 is first calculated with $L_0 = 1$, as below:

$$S_0 = \max(\boldsymbol{A}^H\mathbf{y}, L_0) \tag{7}$$

Then, the following expression is evaluated to check its correctness:

$$\|\boldsymbol{A}_{S0}^T\mathbf{y}\|_2 < \frac{1 - \delta_s}{\sqrt{1 + \delta_s}}\|\mathbf{y}\|_2 \tag{8}$$

Here, the constant δ_s is limited between 0 and 1. If the condition is satisfied, the L_0 is incremented by one, and S_0 is updated respectively. Otherwise, the L_0 is considered as the initial sparsity level. This value helps to reduce the number of iterations of the algorithm, leading to speed enhancement.

The pseudo-code related to this algorithm is presented below:

Algorithm 2: Improved Correlation Coefficient Sparsity Adaptive Matching Pursuit (ICCSAMP)

Input params: measurement signal $\mathbf{y}$, sensing matrix $\boldsymbol{A}$, initial step-size s_0

Output: recovered signal $\hat{\mathbf{x}}$

Initial: $\hat{\mathbf{x}} = 0;\ C_0 = \emptyset;\ F_0 = \emptyset; L_0 = 1;\ t = 1;$

//pre-estimation phase

while(true)

$S_0 = \max(\boldsymbol{A}^H\mathbf{y}, L_0)$

  if $(\|\boldsymbol{A}_{S0}^T\mathbf{y}\|_2 < ((1-\delta_s)/\sqrt{1+\delta_s})\|\mathbf{y}\|_2)$

$L_0 = L_0 + 1;$

else $break$;

end while

  $L = L_0;$

$\mathbf{r_0} = \mathbf{y} - \boldsymbol{A}_{S_0}\boldsymbol{A}_{S_0}^{\dagger}\mathbf{y}$

//body

while $(true)$

$S_t = \max(\boldsymbol{A}^H\mathbf{r}_{t-1}, L)$

$C_t = F_{t-1} \cup S_t$

$F = \max(\boldsymbol{A}_{C_t}^{\dagger}\mathbf{y}, L)$

$\mathbf{y}_{C_t} = \boldsymbol{A}_{C_t}(\boldsymbol{A}_{C_t}{}^{\boldsymbol{T}}\boldsymbol{A}_{C_t})^{-\mathbf{1}}\boldsymbol{A}_{C_t}{}^{\boldsymbol{T}}\ \mathbf{y}$

$\mathbf{y}_F = \boldsymbol{A}_F(\boldsymbol{A}_F{}^{\boldsymbol{T}}\boldsymbol{A}_F)^{-\mathbf{1}}\boldsymbol{A}_F{}^{\boldsymbol{T}}\ \mathbf{y}$

$\rho_t = corr(\mathbf{y}_{C_t}, \mathbf{y}_F)$

$\mathbf{if}(\rho_t < 0.9)\ \mathbf{then}$

  $s = s_0 + 10 * (1 - \rho_t)$

$\mathbf{else\ if}\ (\rho_t < 1 - 10^{-6})\ \mathbf{then}$

  $s = s_0$

$\mathbf{else}$

  $s = 1$

$\mathbf{r} = \mathbf{y} - \boldsymbol{A}_F\boldsymbol{A}_F^{\dagger}\mathbf{y}$

  if $\|\mathbf{r}\|_2 < \varepsilon$

    break;

  else if $\|\mathbf{r}\|_2 \geq \|\mathbf{r}_{t-1}\|_2$

    $L = L + s$

  else

    $F_t = F; \mathbf{r}_t = \mathbf{r}; t = t + 1;$

end while

$\hat{\mathbf{x}} = (\boldsymbol{A}_{F_t}{}^{\boldsymbol{T}}\boldsymbol{A}_{F_t})^{-\mathbf{1}}\boldsymbol{A}_{F_t}{}^{\boldsymbol{T}}\ \mathbf{y}$

end

B. Acceptance Criteria in Noisy Condition

Given the sensing matrix $\boldsymbol{A}$, the measurement vector $\mathbf{y}$, and the set of indices S, when the number of measurements M is much smaller than the length of the signal N, in each iteration, reconstructing the signal at specific indices leads to a set of underdetermined equations. Thus, least-squares techniques play a key role in the projection of the samples onto the signal domain.

An important issue that should not be neglected is the performance of least-squares techniques under noisy conditions. In the presence of measurement noise, the observation model is given by

$$\mathbf{y} = \boldsymbol{A}\mathbf{x} + \mathbf{n} \tag{9}$$

where $\mathbf{n}$ is additive zero-mean Gaussian noise with variance σ^2, same as below:

$$\mathbf{n} = \mathcal{N}(0, \sigma^2\boldsymbol{I}) \tag{10}$$

In the Least square technique, the target is to find $\hat{\mathbf{x}}$ which can minimize the residual error $\mathbf{r}$.

$$\mathbf{r} = \mathbf{y} - \boldsymbol{A}\hat{\mathbf{x}} \tag{11}$$

However, the variance of the residual $\mathbf{r}$, $var(\mathbf{r})$, is often found to be greater than the variance of the noise σ^2. In other words, when applying the Least Mean Square method for finding $\hat{\mathbf{x}}$, there is always some stable error remaining which prevents the Mean Square Error (MSE) from becoming lower than the noise variance [30].

As mentioned before, the stopping condition in CCSAMP checks whether the residual norm is lower than a predefined fixed epsilon, typically equal to 10^{-6}. This fixed threshold can cause the algorithm to fail under noisy conditions. However, if the threshold is chosen based on the noise variance, the success rate of the algorithm will increase.

Experimental Results

All evaluation procedures in this article were performed using simulations in MATLAB R2021a.

To ensure a meaningful comparison among different algorithms, a unique test condition was established. Specifically, a K-sparse signal $\mathbf{x}$ was created by generating a random Gaussian signal with a length of N=256 and retaining only K randomly located elements.

To compress this signal by a compression ratio of 50%, a sensing matrix $\boldsymbol{A}$ of size 128×256 was generated, with its elements drawn from a Gaussian distribution. This structure, with high probability, ensures that this sensing matrix satisfies the RIP condition.

The measurement vector $\mathbf{y}$ is created by taking samples from $\mathbf{x}$ by multiplying it with $\boldsymbol{A}$. Given $\mathbf{y}$ and $\boldsymbol{A}$, In this section, the target is to compare the performance of recovery algorithms for estimating $\mathbf{x}$.

One measure to evaluate the performance of the algorithms is the success rate. In order to calculate this measure, for different values of the sparsity K, each recovery algorithm was repeated 500 times with different sparse signals, and the percentage of successful recovery was recorded. The result of recovery is considered successful whenever the norm of residual becomes less than a predefined epsilon.

In the first experiment, signals with different sparsity levels K, ranging from 10 to 50, were generated. The test was repeated for 512 times, and as shown in Fig. 1, the pre-estimation phase in ICCSAMP could decrease the number of iterations in average, while maintaining the success rate unchanged.

However, a slight difference in the success rate under highly sparse conditions ($K = 10$) is due to the value of the estimation parameter δ_0. The effect of this parameter on the success rate is illustrated in Fig. 2. In the case of selecting a small δ_0, the estimation of the sparsity level fails. From this figure, it can be concluded that values above 0.3 perform well for different sparsity levels.

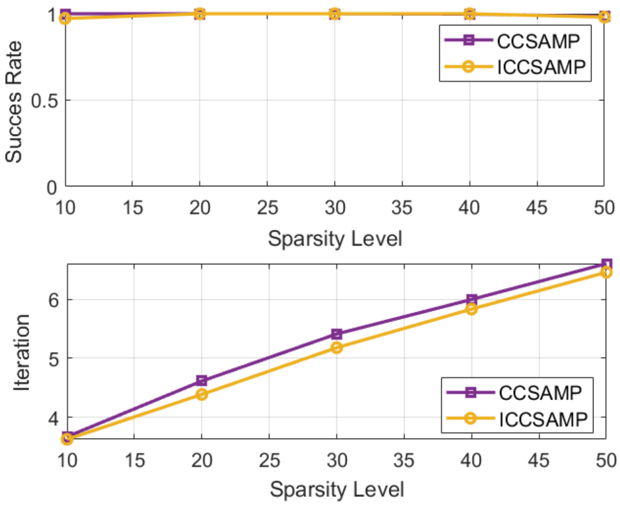

Fig. 1: Performance comparison of the CCSAMP and ICCSAMP without noise. (a) Success Rate (b) number of required iterations.

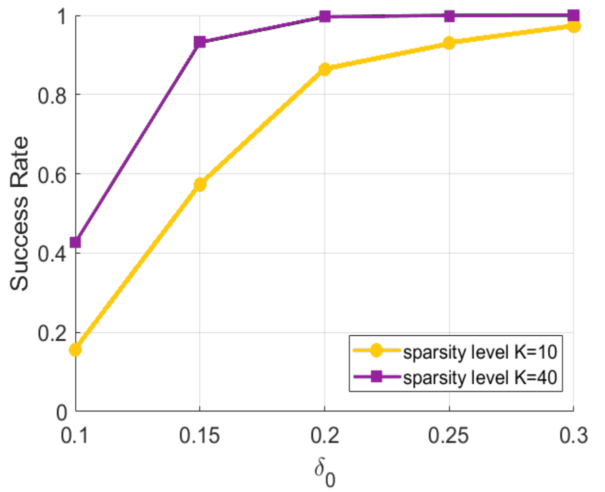

Fig. 2: Effect of δ_0 value on the success rate for sparsity levels of 10 and 40.

As is depicted in Fig. 3, it is noted that in the absence of measurement noise, both of methods, CCSAMP and ICCSAMP, reach the same level of the MSE. This can be concluded that the pre-estimation phase can increase the speed of algorithm, retaining the recovery error the same.

In another experiment, the number of iterations of the SAMP, SAMPVSS, CCSAMP, and ICCSAMP were compared in terms of different sparsity levels. In this test, the initial sparsity level $s_0 = 4$ was selected to be the same for the four algorithms. For SAMPVSS, the parameters $\alpha = 3$ and $\beta = 2$ were used. As illustrated in Fig. 4, it is evident that the ICCSAMP algorithm, which utilized the pre-estimation phase, requires fewer iterations than the other algorithms, resulting in an increase in the overall speed of the recovery process.

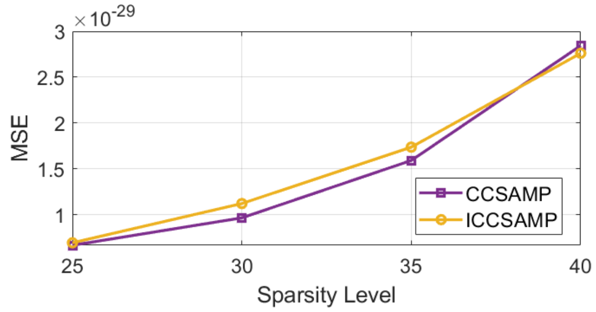

Fig. 3: MSE comparison of the CCSAMP and ICCSAMP without noise.

In another experiment, the number of iterations of the SAMP, SAMPVSS, CCSAMP, and ICCSAMP were compared in terms of different sparsity levels. In this test, the initial sparsity level $s_0 = 4$ was selected to be the same for the four algorithms. For SAMPVSS, the parameters $\alpha = 3$ and $\beta = 2$ were used. As illustrated in Fig. 4, it is evident that the ICCSAMP algorithm, which utilized the pre-estimation phase, requires fewer iterations than the other algorithms, resulting in an increase in the overall speed of the recovery process.

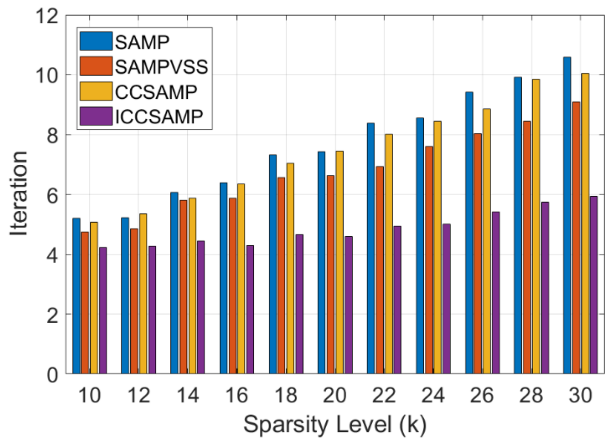

Fig. 4: Comparison of the number of required iterations in different sparsity levels for SAMP, SAMPVSS, CCSAMP, and ICCSAMP.

In the final experiment, our aim was to verify the effect of the presented modified acceptance criteria by comparing the performance of CCSAMP and ICCSAMP under noisy conditions. Meanwhile, to verify that the performance of the presented algorithm remains consistent across signals with different lengths, we conducted this test using an input signal of length 512.The success rate, number of iterations, and the mean squared error (MSE) of the recovery error are illustrated in the Fig. 5.

It is evident that in the presence of Gaussian measurement noise with various SNR levels, the CCSAMP algorithm with fixed stop criterion of 10^{-5} was unable to perform, having a success rate below 0.6 in various SNR levels. In contrast, the ICCSAMP algorithm could successfully recovered the signal. As shown, for ICCSAMP, both the MSE and the number of iterations decrease as the SNR increases. Specifically, in SNR higher than $20dB$, the MSE of the CCSAMP is nearly zero which proves that the signal could be recovered with high accuracy. This behavior can be explained by the fact that greedy algorithms operate iteratively. If the acceptance criterion is not chosen appropriately, the algorithm is likely to fail in detection of the correct sparsity level. Neglecting noise variance and using a fixed value for epsilon increases the likelihood of failure, particularly in low SNR conditions.

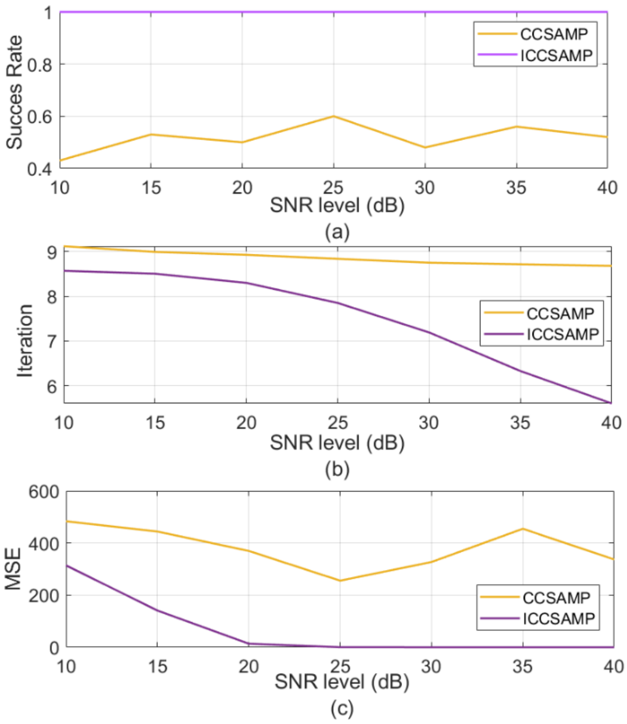

Fig. 5: Performance comparison of CCSAMP and ICCSAMP in different SNRs. (a) success rate (b) number of required iterations (c)MSE.

Discussion

All the experiments in this article are conducted using a white Gaussian signal as the input, which follows a normal distribution. It is important to note that if other distributions, such as Cauchy sequences with outlier values, are used, the performance may be affected. During the sparsification process if outlier values are selected, the recovery process becomes more challenging. This is because greedy algorithms operate by selecting columns of the sampler matrix that have higher correlation with the samples. In this phase, outliers tend to dominate, which can significantly affect the atom selection process.

In an experiment, we generated two sets of input based on the Gaussian and Cauchy distribution, and repeated the algorithm for 512 times. The below table also implies on the above-mentioned discussion.

Table 1: ICCSAMP performance with two different inputs

Input distribution	Success rate	MSE
Gaussian	0.88	42.407
Cauchy	0.51	1.59×10^5

Summary and Conclusion

In sub-Nyquist sampling methods such as MWC, sparse recovery algorithms are essential for the blind recovery process. Although most greedy recovery algorithms require knowing the sparsity level in advance, a group of algorithms, known as SAMP algorithms, can adaptively recover the signal by adjusting the sparsity level in each iteration. The initial value of the sparsity level in SAMP algorithms can highly affect their performance due to either overestimation or underestimation. Also, the way the step-size is adjusted can change the computational time of the algorithm. In our proposed method, we not only reduced the number of required iterations by integrating a pre-estimation phase, but also increased the success rate of the algorithm in noisy conditions by implementing a modified stopping criterion, based on the variance of the white gaussian noise.

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Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Authors' Contribution

Azadeh Vakili: Conceptualization, Investigation, Software, Methodology, Validation, Writing - original draft. Mohammad Shams Esfand Abadi: Project administration, Supervision, Validation, Writing - review & editing. Mohammad Kalantari: Project administration, Supervision, Validation, Writing - review & editing.

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Abbreviation

$\mathbf{A}$	*Sensing matrix*
$(.)^H$	*Hermitian transpose of argument matrix*

$(.)^{\dagger}$	*Pseudo inverse of argument matrix*
$\boldsymbol{A}_F$	*Columns of $\boldsymbol{A}$ corresponding to index set F*
$\hat{\boldsymbol{x}}$	*Estimated recovered signal*
$\|\ \|_0$	*l_0 −norm*
$\|.\|_2$	*Euclidean norm*
$corr(\boldsymbol{x},\boldsymbol{y})$	*Correlation between $\boldsymbol{x}$ and $\boldsymbol{y}$*
$var(.)$	*Variance of elements of argument vector*
RIP	*Restricted Isometry Property*
$\boldsymbol{n}$	*Measurement noise*
$\boldsymbol{y}$	*Compressed samples*
MSE	*Mean Square Error*
K	*True sparsity level*
L	*Estimated sparsity level*
SNR	*Signal to Noise Ratio*
SAMP	*Sparsity Adaptive Matching Pursuit*
CCSAMP	*Correlation Calculation SAMP*

References

[1] J. Kang, H. Yoon, C. Yoon, S. Emelianov, "High-frequency ultrasound imaging with sub-nyquist sampling," IEEE Trans. Ultrason. Ferroelectr. Freq. Control, 69(6): 2001-2009, 2022.

[2] D. Cohen, Y. C. Eldar, "Sub-nyquist radar systems: Temporal, spectral, and spatial compression," IEEE Signal Process. Mag., 35(6): 35-58, 2018.

[3] C. Wang, S. Ling, "An image encryption scheme based on chaotic system and compressed sensing for multiple application scenarios," Inf. Sci., 642, 119166, 2023.

[4] Y. C. Eldar, Compressed Sensing. in: Sampling Theory Beyond Bandlimited Systems, Cambridge University Press. 608-628, 2015.

[5] D. L. Donoho, "Compressed sensing," IEEE Transa. Inf. Theory, 52(4): 1289-1306, 2006.

[6] E. J.Candes, J. Romberg, T. Tao, "Robust uncertainty principles: Exact signal reconstruction from highly incomplete frequency information," IEEE Trans. Inf. Theory, 52(2): 489-509, 2006.

[7] E. C. Marques, N. Maciel, L. Naviner, "A review of sparse recovery algorithms," IEEE Access, 7: 1300-1322, 2019.

[8] S. Chen, D. L. Donoho, M. A. Saunders, "Atomic decomposition by Basis Pursuit," SIAM J. Sci. Comput., 20(1): 33-61, 1999.

[9] R. Tibshirani, "Regression shrinkage and selection via the lasso," J. R. Stat. Soc., 58(1): 267-288, 1996.

[10] S. Ji, Y. Xue, L. Carin, "Bayesian compressive sensing," IEEE Trans. Signal Process., 56(6): 2346-2356, 2008.

[11] S. G. Mallat, Z. Zhang, "Matching pursuits with time-frequency dictionaries," IEEE Trans. Signal Process., 41(12): 3397-3415, 1993.

[12] Y. Pati, R. Rezaifar, P. Krishnaprasad, "Orthogonal matching Pursuit: Recursive function approximation with applications to wavelet decomposition," in Proc. Asilomar Conference on Signals, Systems, and Computers, Pacific Grove, 1993

[13] W. Dai, O. Milenkovic, "Subspace pursuit for compressive sensing signal reconstruction," IEEE Trans. Inf. Theory, 55: 2230-2249, 2009.

[14] D. Needell, J. A. Tropp, "CoSaMP: Iterative signal recovery from incomplete and inaccurate samples," Appl. Comput. Harmon. Anal., 26(3): 301-321, 2008.

[15] T. Blumensath, M. Davies, "Gradient pursuits," IEEE Trans. Signal Process., 56(6): 2370-2382, 2008.

[16] Q. Wang, G. Qu, "A new greedy algorithm for sparse recovery," Neurocomputing, 275: 137-143, 2018.

[17] T. Do, L. Gan, "Sparsity adaptive matching pursuit algorithm for practical compressed sensing," in Proc. Conference on Signals, Systems, and Computers, 2008.

[18] R. Yan, Q. Li, H. Xiong, "Mitigating impulsive noise in airborne PLC: Introducing the S-SAMP-PV algorithm for MIMO OFDM systems," Signal Process., 230, 109798, 2025.

[19] Z. B. Lahaw, H. Seddik, "A new greedy sparse recovery algorithm for fast solving sparse representation," Visual Comput., 38: 2431-2445, 2022.

[20] S. Yao, Q. Guan, S. Wang, "Fast sparsity adaptive matching pursuit algorithm for large-scale image reconstruction," EURASIP J. Wireless Commun. Networking, 78, 2018.

[21] Z. Liquan, M. Ke, J. Yanfei, "Improved generalized sparsity adaptive matching pursuit algorithm based on compressive sensing," J. Electr. Comput. Eng., 2020, 2782149, 2020.

[22] Y. Zhang, Y. Liu, X. Zhang, "A variable step-size sparsity adaptive matching pursuit algorithm," IAENG Int. J. Comput. Sci. 48(3), 2021.

[23] C. Wang, Y. Zhang, L. Sun, "Improved sparsity adaptive matching pursuit algorithm based on compressed sensing," Displays, 77, 102396, 2023.

[24] Y. Fu, S. Liu, C. Ren, "Adaptive step-size matching pursuit algorithm for practical sparse reconstruction," Circuits Syst. Signal Process., 36: 2275-2291, 2017.

[25] Y. Li, W. Chen, "A correlation coefficient sparsity adaptive matching pursuit algorithm," IEEE Signal Process. Lett., 30: 190-194, 2023.

[26] X. Wang, Y. Jiang, G. Ding, "An improved variable step SAMP method based on correlation principle," Electronics,13(22),4502, 2024.

[27] E. J. Candes, T. Tao, "Decoding by Linear Programming," IEEE Trans. Inf. Theory, 51(12): 4203-4215, 2005.

[28] J. Tropp, S. Wright, "Computational methods For sparse solution of linear inverse problems," Proc. IEEE, 98(6): 948-958, 2010.

[29] X. Zhang, Y. Liu, X., Wang, "A sparsity pre-estimated adaptive matching pursuit algorithm," J. Electr. Comput. Eng., 2021, 5598180, 2021.

[30] M. H. Hayes, Statistical Digital Signal Processing and Modeling, John Wiley and Sons, Canada, 1996.

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