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An Improved Regularized Adaptive Matching Pursuit Algorithm Based on LDPC Matrix

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Abstract

Compressed sensing theory breaks the traditional sampling limit. It projects the high-dimensional signal into a low-dimensional space to get a small number of measured values through the observation matrix, and then uses the reconstruction algorithm to get the original signal with high probability. In order to solve the problem of unknown signal sparsity in practical applications, it is proposed an improved regularized adaptive matching pursuit algorithm based on LDPC measurement matrix. In the case of unknown sparsity, it is used the LDPC matrix with quasi-cyclic characteristic for observation in the improved algorithm, which sets adaptive threshold automatically to adjust the number of atoms of candidates, and passes back to eliminate error atoms. At the same time, the LDPC matrix corresponding to the new atomic number is updated to improve the accuracy of reconstruction. The experimental results show that the step size can gradually approach the value of sparsity, so as to reconstruct the original signal accurately under the premise of unknown sparsity and the same test conditions. Thus it can ensure the global optimization and reduce the reconstruction time. In addition, because the selected LDPC observation matrix is quasi-cyclic, the storage space of the observation matrix can be saved, which is beneficial to hardware implementation, and these provide a better implementation method for the practical application of compressed sensing theory.

Keywords*: compressed sensing, signal reconstruction, matching pursuit, regularization, LDPC, adaptive threshold*

I. Introduction

As a new theory in the field of signal processing, compressed sensing has attracted more and more attention from researchers in related fields. The theory breaks through the traditional Nyquist sampling theorem in the way of signal acquisition. The data got by the observing matrix is compressed properly to get a small amount of measured values. It can overcome the shortcomings of the traditional sampling method, such as large amount of data, long time consuming and taking up huge storage space. The theory will have more broad application prospects in the field of signal processing.

One of the key problems of compressed sensing is the design of signal reconstruction algorithm, which should be able to reconstruct the original signal quickly, statically, efficiently, accurately or approximately precisely by use of as few compressed measured values as possible [1]. Traditional signal reconstruction algorithms mainly fall into three categories: convex optimization (relaxation) algorithm, greedy algorithm, and Bayesian statistical optimization algorithm. Among them, convex optimization algorithms mainly include interior point method, least absolute shrinkage and selection operator (LASSO) algorithm [2], the least angle regression (LARS) algorithm [3], gradient projection (GP) algorithm [4], soft/hard iterative threshold (SIT/HIT) algorithm [5] and other sparse reconstruction algorithms, which solve signal approximation by converting non-convex problems into convex ones. It has the characteristics of small reconstruction error and good reconstruction effect, but it has high complexity, large amount of calculation and long reconstruction time. However, it is difficult to apply for large-scale problems and has poor practicability.

Greedy algorithms mainly include match Pursuit (MP) algorithm [6], orthogonal match Pursuit (OMP) algorithm [7], regularized Orthogonal match Pursuit (ROMP) algorithm[8], subspace pursuit(SP) algorithm [9], compressed sampling matching pursuit (CoSaMP) algorithm [10], stagewise orthogonal match pursuit (StOMP) algorithm [11], sparsity adaptive matching pursuit (SAMP) algorithm [12], and regularized adaptive matching pursuit (RAMP) [13] algorithm. This kind of algorithm selects the optimal matching atom from the measurement matrix in each iteration process to perform sparse approximation to the original signal. The algorithm has relatively low computational complexity, fast operation speed, good reconstruction effect and is easy to implement and widely used. However, compared with the convex optimization algorithm, more compression measurements are needed and the reconstruction accuracy is relatively low.

Bayesian statistical optimization algorithm mainly includes FOCal Underdetermined System Solver (FOCUSS) algorithm [14] based on l_p norm and reweighted algorithm with iterative support detection (RISD) [15], where $0<p<1$. The number of compression measurements, the computational complexity and the accuracy of signal reconstruction required by this kind of algorithm are generally between the relaxation and greedy algorithms.

II. Research Status of Signal Reconstruction Algorithms

In recent years, many scholars have studied the improvement and application of signal reconstruction algorithm. In 2016, the regularized LASSO estimation based on l_1 norm and basis tracking denoising algorithm for the compressed sensing of noisy signals were studied, and the regularization problem of l_2 norm and l_0 norm were discussed [16]. A backtracking regularized adaptive matching pursuit (BRAMP) algorithm was proposed to reconstruct the original signal when the sparsity is unknown. The adaptive threshold was used to screen atoms, and the backtracking method was used to eliminate the wrong atoms selected from the support set so as to improve the reconstruction accuracy [17].
On the purpose of reducing hardware complexity of OMP algorithm, two different modifications to OMP algorithm named Thresholding technique for OMP (tOMP) and gradient descent OMP (GDOMP) were proposed in 2017. TOMP algorithm modified identification stage of OMP algorithm to reduce reconstruction time and GDOMP algorithm modified residual update phase to reduce chip area [18]. Based on the backtracking idea of subspace tracking (SP) algorithm, conjugate gradient descent algorithm was used instead of least square method to improve the orthogonal matching tracking (OMP) algorithm, so as to ensure good reconstruction quality and better reconstruction speed and stability [19].

For the problems of large time overhead and low reconstruction success probability, an improved orthogonal complement space matching and tracking algorithm was proposed in 2018. The fuzzy threshold method was used to select the atoms of the support set, which reduced the number of reconstruction iterations and accelerated the convergence speed [20].An accelerated multipath matching pursuit (MMP) algorithm to reduce the running time was proposed in 2019, which adopted the strategy of pruning trees to improve the existing MMP algorithm [21].

From the references in recent years, it can be seen that there is less amount of calculation of sampling, and larger amount of calculation of restruction in the compressed sensing. The research on signal reconstruction algorithm mainly lies in how to make a trade-off between the reconstruction effect and computational complexity, how to select good observation matrix, and how to approach signal sparsity that is usually unknown in the practical application. These are hot issues in academic research. To solve these problems, this paper proposes an improved regularized adaptive matching Pursuit (IRAMP) algorithm based on LDPC measurement matrix. In this algorithm, the LDPC matrix with quasi-cyclic characteristics is used for observation [22], and the number of candidate set atoms is automatically adjusted by the adaptive threshold to improve the accuracy of reconstruction and reduce the reconstruction time when the signal sparsity is unknown.

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III. Compressed Sensing of Signals

The reconstruction process of compressed sensing is shown in Figure 1. In the theory, the sampling and compression coding of signals take place in the same step, and the signal sparsity is utilized to conduct non-adaptive measurement coding at a rate far lower than the Nyquist sampling rate. Each measured value is a combination function of each sample signal under the traditional theory, that is, a measured value contains a small amount of information about all sample signals. The decoding process is not a simple inverse process of coding. Instead, the existing reconstruction methods in signal sparse decomposition are used to achieve precise signal reconstruction or approximate signal reconstruction with a certain error in the sense of probability. The number of measured values required for decoding is far less than the number of samples under the traditional theory.

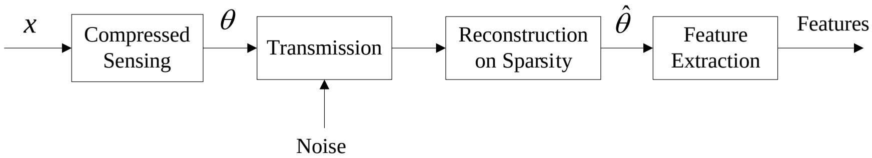

Fig 1: Signal reconstruction process of CS theory

In the compressed sensing reconstruction algorithm, it is assumed that the original signal x can be sparsely represented as θ in the wavelet domain, $x \in R^N$, And there exists a set of sparse orthogonal basis $\Psi = (\psi_1, \psi_2, \cdots, \psi_N)_{N\times N}$, then the signal x can be expressed as:

$$x = \Psi\theta \tag{1}$$

Where, x is N dimensional row vector, $\theta = (\theta_1, \theta_2, \ldots, \theta_N)^T$, $\theta_i = \langle x, \psi_i \rangle$.

If Φ is set to be the measurement matrix, then $\Phi=(\phi_1, \phi_2, \cdots, \phi_\mathrm{N})$, and $\phi_k = (\varphi_{1,k}, \varphi_{2,k}, \cdots, \varphi_{N,k})^T$, $k = 1, 2, \cdots, N$; Ψ is the orthogonal basis dictionary matrix, and the measured value y after compressed sensing observation is:

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

Here, y is M dimensional row vector, A is the sensing matrix of size $M \times N$, and $M << N$.

The non-correlation between the sparse orthogonal basis and the measurement matrix is defined as:

$$\mu(\Phi, \Psi) = \sqrt{N} \max_{1\le k, j\le N} \left| \langle \phi_k, \psi_j \rangle \right| \tag{3}$$

Where, $1 \le \mu(\Phi, \Psi) \le \sqrt{N}$. The smaller $\mu(\Phi, \Psi)$ is, the fewer measurements are required in compressed sensing, that is, the less Φ correlated with Ψ .

If θ is K-sparse under a sparse basis Ψ that is not related to the measurement matrix Φ , the measured value y is known and satisfies:

$$m \ge C \cdot \mu^2(\Phi, \Psi) \cdot K \cdot \log n \tag{4}$$

Then its signal recovery can be equivalent to a minimization problem of l_0 norm, C is a constant approximately 2.

When the measurement matrix Φ satisfies the constraint isometric constraint RIP criterion, the recovery of compressed sensing signals can be equivalent to a l_1 norm minimization problem, and then the compressed sensing recovery algorithm based on l_1 norm minimization is the optimal solution of solving the normal problem

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through Equation (5) :

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

According to Equation (5), an approximate representation of the sparse coefficient in the sparse matrix can be obtained.

IV. Improved Adaptive Matching Pursuit Algorithm Based on LDPC

4.1 Construction of LDPC measurement matrix based on finite field

A line i in finite geometry corresponds to a N weight vector $\boldsymbol{V}_i = \{v_{i1}, v_{i2}, \cdots v_{iN}\}$, When the point j is on the line i, it can be got $v_{ij} = 1$. $\boldsymbol{V}_i$ is called the associated vector of the line i, which has a weight of ρ. The matrix $\boldsymbol{H}_{M\times N}$ would be formed by N points, M lines and their associated vectors in finite geometry.

For any finite geometric domain that exists, if there are N points and M lines, it can be constructed the vector $\boldsymbol{V} = \{v_1, v_2, \cdots v_N\}$ on GF (2) corresponding to points. Geometric domain in a straight line corresponds to a weight vector, when the first point on the line,. The associated vector, called the line, has a weight of. So points, lines and their associated vectors in a finite geometry form a matrix.

The density of the matrix $\boldsymbol{H}_{M\times N}$ is $\rho / N = \lambda / M$, When ρ and λ are very small relative to N and M, $\boldsymbol{H}_{M\times N}$ is a sparse low density matrix, its null space forms the LDPC code. The steps of LDPC measurement matrix construction algorithm are as follows:

First, the cyclic transposon matrix $\boldsymbol{A}$ is determined. The $\boldsymbol{H}$ of the quasi-cyclic LDPC code is composed of many cyclic submatrices, each of which is a square matrix with the size $q \times q$.

Secondly, the basis matrix is constructed

$$H_b = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_m \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m0} & a_{m1} & \cdots & a_{mn} \end{bmatrix} \tag{6}$$

Here, $a_{ij} \in (0,1)$, $i = 1,2,\cdots m; \ j = 1,2,\cdots n$.

Next, the matrix P of shift number should be determine.

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{m1} & p_{m2} & \cdots & p_{mn} \end{bmatrix} \tag{7}$$

Each element of the basis matrix is extended to a square matrix of size $q \times q$, element 0 is represented by a zero square matrix, and element 1 is represented by a cyclic shift square matrix $\boldsymbol{I}$, and element ∞ is represented by a zero matrix of the corresponding cyclic shift matrix.

Finally, the basis matrix is extended to the check matrix *H*, Each element of the basis matrix H is replaced by the corresponding cyclic substitution matrix, $H_b(p_{ij})$ represents a zero matrix of size $q \times q$ or the cyclic submatrix $I(p_{ij})$ obtained by rotating the identity matrix to the right p_{ij} times.

$$H = \begin{bmatrix} H_b(p_{11}) & H_b(p_{12}) & \cdots & H_b(p_{1n}) \\ H_b(p_{21}) & H_b(p_{22}) & \cdots & H_b(p_{2n}) \\ \vdots & \vdots & \ddots & \vdots \\ H_b(p_{m1}) & H_b(p_{m2}) & \cdots & H_b(p_{mn}) \end{bmatrix} \tag{8}$$

The girth size in Tanner graph of LDPC codes has a great influence on the performance of LDPC codes, especially the short girth with the length 4, so it needs to eliminate the short girth of the check matrix $\boldsymbol{H}$. Thus the parity check matrix of LDPC codes structured in this way would not only be sparse, but also have the system characteristics of the cyclic code or quasi cyclic code, which makes it very suitable for hardware implementation.

4.2 Improved adaptive matching pursuit algorithm

4.2.1 Algorithm analysis

The solution of Equation (5) is an NP-hard problem, which is difficult to solve directly. The matching pursuit method provides a powerful tool for the approximate solution of the problem. Based on the selection criterion of atoms, it implements the recursively normalizing the set of selected atoms to ensure the optimality of iteration by OMP algorithm, so as to reduce the number of iterations. On this basis, ROMP algorithm applies the regularization process to OMP algorithm with known sparsity. The difference between ROMP algorithm and OMP algorithm lies in that the former first selects multiple atoms as the candidate set according to the relevant atoms, then selects some atoms from the candidate set according to the regularization principle, and finally merges them into the final support set. The selection process is rapid and effective.

StOMP algorithm is another improved one of OMP algorithm, each iteration can select more than one atom. There is no signal sparsity K in the input parameter of this algorithm, so it has unique advantages compared with ROMP and CoSaMP. SP algorithm and CoSaMP algorithm introduced the rollback filtering process, so the signal reconstruction quality is good, and the reconstruction complexity is low. CoSaMP algorithm is an improvement of OMP algorithm, and multiple atoms are selected in each iteration. The difference between CoSaMP and ROMP algorithm is that the selected atoms in each iteration of ROMP are always retained, while the selected atoms in each iteration of CoSaMP may be discarded in the next iteration. SP algorithm and CoSaMP algorithm are highly similar, but the difference is that SP algorithm selects K atoms each time, while CoSaMP algorithm selects $2K$ atoms.

The above algorithms are all based on the known sparsity K, but the signal sparsity is often unknown in practical applications. Therefore, the sparsity adaptive matching pursuit (SAMP) algorithm appears. By setting a variable step size, the signal sparsity is estimated step by step, and the reconstruction effect is better and the speed is much faster than OMP algorithm. On the basis of ROMP algorithm, the RAMP algorithm combines with the adaptive idea of SAMP algorithm to automatically adjust the number of selected atoms in the iteration process to reconstruct the unknown signal, which can ensure the signal reconstruction quality and reduce the running time. In this paper, a cyclic LDPC matrix is constructed for observation. On the basis of RAMP algorithm, the number of selected atoms is automatically adjusted in the iteration process to reconstruct the signal with unknown sparsity. It is taken the method of phase transformation which can increase the number of atoms gradually, and the same iteration process is divided into multiple stages. It is set a variable step size instead of the selected number of atoms, and make a backup copy of LDPC matrix content. After each iteration, it will back out of atoms corresponding to zero matrix column, and read the backup information of LDPC observation matrix for signal recovery. With the increase of step size and support set, the step size is gradually approximating K under the premise of unknown

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sparsity. In this way, the original signal can be reconstructed accurately and the operation speed of the algorithm will be improved.

4.2.2 Steps of IRAMP Algorithm

The symbols defined are as follows: It is defined t as the number of iterations. Λ_t is the set of column ordinals for iteration t. λ_t represents the column number found in iteration t. a_j is defined as the column j of compressed sensing matrix A, and A_t represents the set of columns of matrix A selected by index Λ_t. J is a collection of column ordinals, J_0 represents the column ordinals found in each iteration, $\langle \cdot,\cdot \rangle$ stands for the inner product of a vector. s and n represent the transformation phase and step size respectively. α and β represent the thresholds for controlling the number of iterations and phase transformation respectively.

Input: Compressed sensing matrix $A \equiv \Phi\Psi$, $A \in C^{M\times N}$, Measurement vector $y = \Phi x = \Phi\Psi\theta = A\theta$, $y \in C^M$, $x \in C^N$,

Output: Coefficient estimation $\hat{\theta}$ of signal sparse representation, Residual error: $r_k = y - A_k \cdot \hat{\theta}_k$.

Step 1, Initialization: Initial residual value $r_0 = y$, initial step $n \neq 0$,transition stage s=1, the number of iterations $t = 1$, Set of index values $\Lambda_0 = \varnothing$, $A_0 = \varnothing$, $J = \varnothing$.

Step 2, Recognition: Calculate the correlation coefficient $u = \langle r_{t-1}, a_j \rangle, 1 \le j \le N$,When the number of non-zero coordinates is less than n, select all non-zero values in u, When that is greater than or equal to n, select n of the maximum values. Set the index values corresponding to the selected values J.

Step 3, Regularization: Look for a subset J_0 of the set J, $J_0 \subset J$, which meet the conditions: $|u(i)| \le 2|u(j)|$, $i, j \in J_0$; Select the subset J_0 of all satisfying subsets with the maximum energy $\left\| u|_{J_0} \right\|_2$.

Step 4, Backup the contents of LDPC observation matrix Φ.

Step 5, Update the observation matrix to ensure the orthogonality between the selected atom and the residual, $\left\{ \Phi_\lambda = 0 \middle| \lambda \in J_k \right\}$.

Step 6, Update the support set: $\Lambda_t = \Lambda_{t-1} \cup J_0$, $A_t = A_{t-1} \cup a_j$ ($j \in J_0$).

Step 7, Find the least-squares solution of the equation $y = A_t \cdot \theta_t$, $\hat{\theta}_t = \arg\min_{\theta_t} \| y - A_t\theta_t \| = \left(A_t^T A_t \right)^{-1} A_t^T y$.

Step 8, Backtrack atoms in the support set, eliminate errors ones.

Step 9, Restore the column vector of the observation matrix corresponding to the deletion of atoms, that is $\left\{ \Phi_\gamma = \Phi_{1\gamma} \middle| \gamma \in \left(\Lambda_k \text{-} I_k \right) \right\}$.

Step 10, Update the residual: $r_t = y - A_t\hat{\theta}_t = y - A_t(A_t^T A_t)^{-1} A_t^T y$.

Step 11, Threshold β judgment: if $\| r_n - r \| \le \beta$, then let $s = s + 1$, $n = n \cdot s$, and return to step 2, otherwise, let $r = r_n$, $t = t + 1$, and return to step 8.

Step 12, Threshold α judgment: if $\| r \|_2 \le \alpha$, then the iteration ends, the resulting atoms are used for the final signal reconstruction, otherwise, return step 2.

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V. Experimental Results

5.1 Reconstruction of one dimensional signal

In this paper, OMP algorithm, ROMP algorithm, StOMP algorithm, SP algorithm, CoSaMP algorithm, SAMP algorithm, RAMP and IRAM algorithm are compared by MATLAB software. The simulation signal used in the experiment is the Gauss random signal with the length 256, and the observation matrix φ is a QC-LDPC matrix constructed based on a finite field, with the size of 128×256, that is, the compression ratio is 0.5. The hardware configuration of the computer is Intel(R) Core(TM) I7-8565 CPU, 1.8GHz main frequency, 8.00GB memory. The software environment is Matlab R2021a under 64-bit Windows10 operating system.

When the sparsity K is equal to 15, the reconstruction results and reconstruction errors of the compressed simulation signals of the 8 classes of greedy algorithms are shown in Figure 2-9 respectively. From the simulation results, it can be seen that ROMP, StOMP and CoSaMP algorithms have large reconstruction errors, and the sparse signals obtained after reconstruction generate a large number of error signals compared with the original signals. OMP algorithm, SP algorithm, RAMP algorithm and SAMP algorithm have little difference in reconstruction effect. IRAMP algorithm has the best reconstruction effect compared with other algorithms, and the reconstructed signal is closest to the original signal.

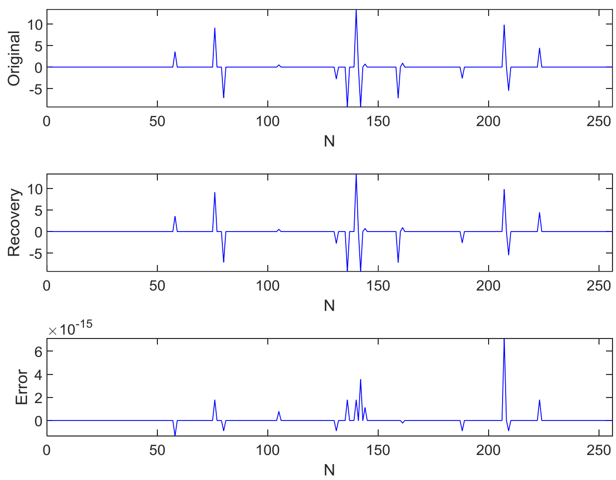

Fig 2: Simulation result of OMP algorithm

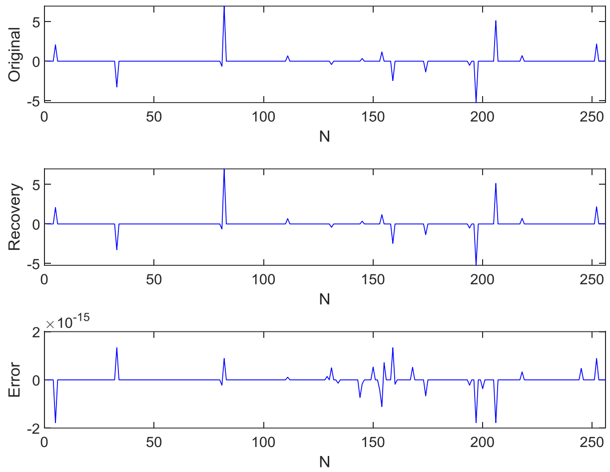

Fig 3: Simulation result of ROMP algorithm

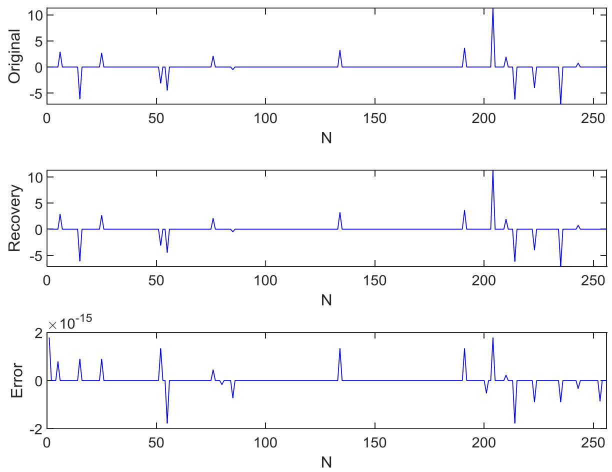

Fig 4: Simulation result of StOMP algorithm

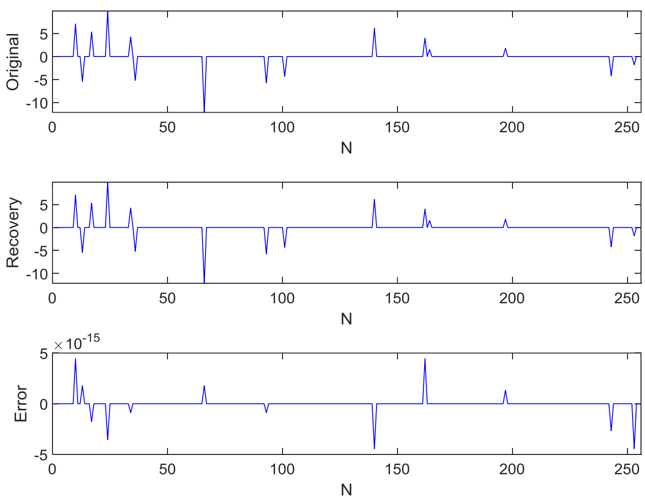

Fig 5: Simulation result of CoSaMP algorithm

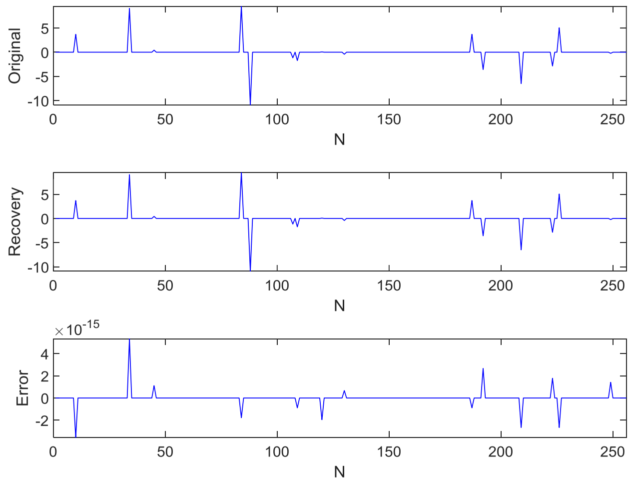

Fig 6: Simulation result of SP algorithm

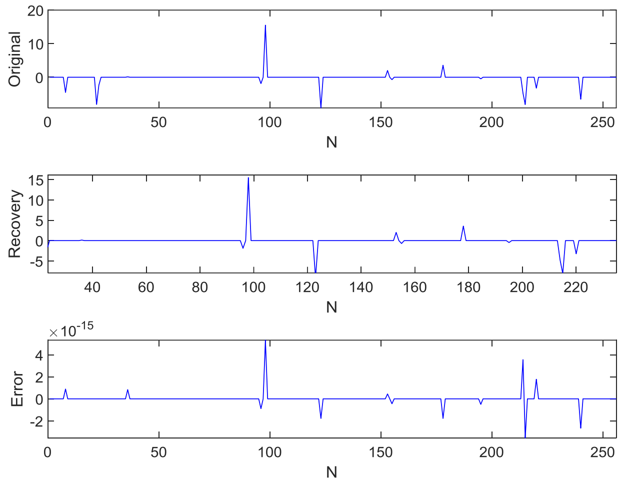

Fig 7: Simulation result of SAMP algorithm

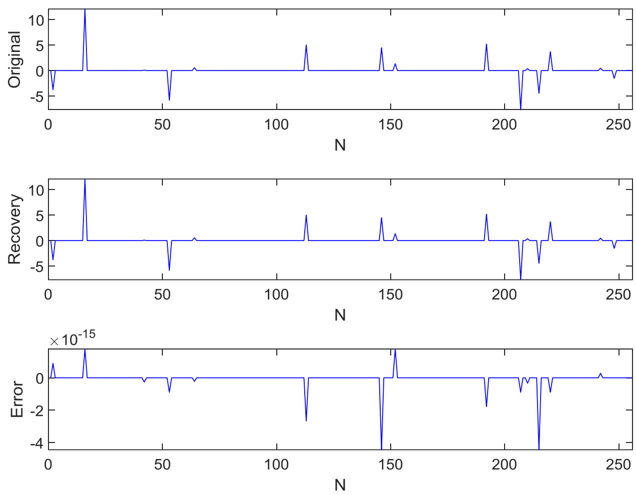

Fig 8: Simulation result of RAMP algorithm

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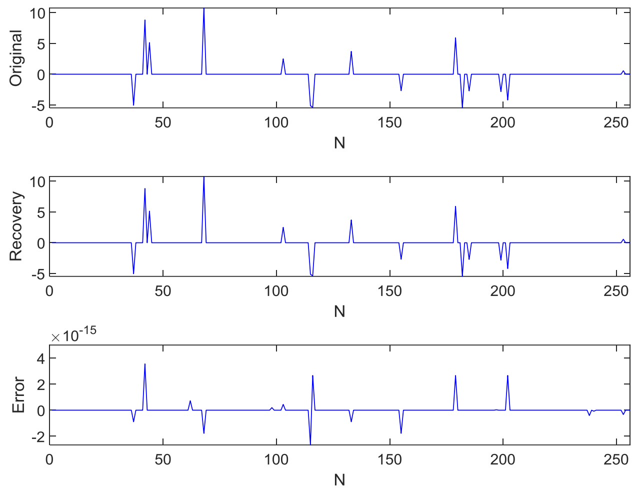

Fig 9: Simulation result of IRAMP algorithm

5.2 Experimental analysis

In the case of different sparsity *K*, the reconstruction accuracy of the 8 greedy algorithms is shown in Figure 10. Under the condition of different sparsity, each algorithm is iterated for 1000 times, and when the residual is less than 1E-6, the original signal is considered to have been successfully reconstructed.

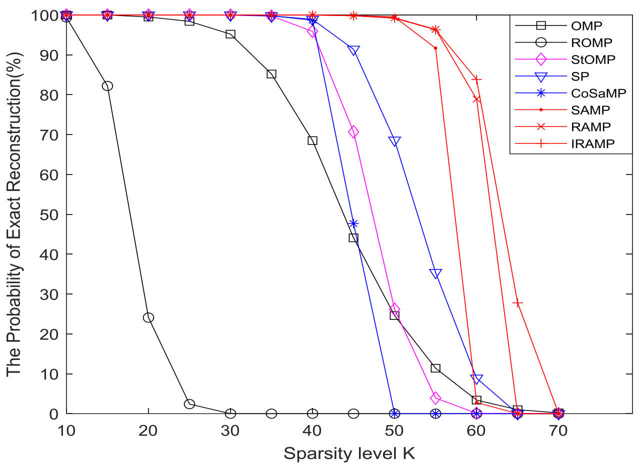

Fig 10: Reconstruction accuracy with different sparsity

As can be seen from Figure 10, ROMP algorithm has the lowest successful reconstruction rate. OMP algorithm is close to StOMP and CoSaMP algorithm, and better than ROMP algorithm. When the sparsity K is 45, the probability of successful reconstruction of OMP and CoSaMP algorithm is approximately equal to 45 percent. When the sparsity K is 50, the probability of successful reconstruction of OMP and StOMP algorithms is approximately equal to 25 percent. The successful reconstruction rate of SP algorithm is better than OMP, StOMP and CoSaMP algorithm. SAMP algorithm is superior to SP algorithm when the sparsity K is less than 60. However, when the sparsity K is greater than 60 and less than 65, SAMP algorithm is slightly worse than SP algorithm. But when the sparsity K is greater than 65 and less than 70, the successful reconstruction rate of both algorithms is basically equal.

The successful reconstruction rate of RAMP and IRAMP algorithm is significantly higher than that of other algorithms, and the success rate of IRAMP algorithm is slightly higher than that of RAMP algorithm. When the sparsity K equals 65, it has a successful reconstruction probability of about 35 percent. This is because the improved IRAMP algorithm sets a variable step size to replace the number of selected atoms, and at the same time, the contents in the LDPC observation matrix are backed up. After each iteration, the matrix column corresponding to the eliminated atoms in the traceback is cleared to zero, and the information of the backup LDPC observation matrix is read for signal recovery. With the increase of step size and support set, the step size is gradually approximating K under the premise of unknown sparsity, which makes the success probability of rebuilding the original signal higher.

When the sparsity K is different, the signal reconstruction of 8 greedy algorithms is carried out for 1000 times respectively. The total running time of each algorithm varies with the sparsity, as shown in Figure 11.

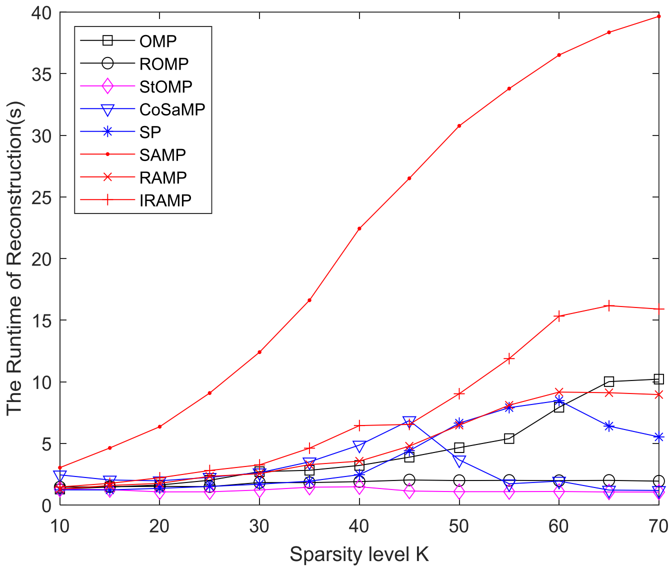

Fig 11: Reconstruction accuracy with different sparsity

As can be seen from Figure 11, in terms of reconstruction time, ROMP and StOMP algorithms are the fastest, followed by OMP, SP and RAMP algorithms. When the sparsity *K* is smaller than 35 or *K* is greater than 55, the reconstruction time of CoSaMP algorithm is close to that of ROMP algorithm. When *K* is greater than 35 and less than 55, SAMP algorithm takes the longest reconstruction time, the reason is that SAMP algorithm needs to set a variable step size on the premise of unknown sparsity to estimate signal sparsity step by step, which makes the operation time long. IRAMP algorithm is located in the middle and takes longer time to reconstruct than RAM algorithm. This is because in order to ensure the reconstruction accuracy, after each iteration, IRAMP algorithm needs to not only backtrack the deleted atoms, and carry out the corresponding matrix column zero-clearing operation, but also read the contents of the backup LDPC matrix, which will increase the amount of computation and operation time. Therefore, the operation time of IRAMP algorithm is longer than that of RAMP algorithm.

VI. Conclusion

In this paper, various classical reconstruction algorithms of compressed sensing theory and the research status in recent years were deeply studied. Aiming at the problem of unknown signal sparsity in practical application, RAMP algorithm was improved. An improved adaptive regularized adaptive matching pursuit (IRAMP) algorithm based on LDPC measurement matrix is proposed. In the case of unknown signal sparsity, it uses the LDPC matrix with quasi-cyclic characteristics for observation, and simple and effective regularization process for filtering the atomic library. At the same time, the signal sparsity is estimated adaptively by setting two iteration thresholds, so that signal reconstruction can be realized for signals with unknown sparsity. The experiment results show that the

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step size can gradually approach the sparsity under the same test conditions. Thus the original signal can be reconstructed accurately, and the reconstruction time can be reduced. In addition, because of using matrix with quasi-cyclic LDPC characteristics, it can not only save the observation matrix storage space, but also reduce the decoding complexity, which is helpful for hardware implementation. These provide a better implementation method for the application of compressed sensing theory.

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