A New Nonconvex Sparse Recovery Method for Compressive Sensing

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As an extension of the widely used $\ell_r$-minimization with $0 < r \leq 1$, a new non-convex weighted $\ell_r - \ell_1$ minimization method is proposed for compressive sensing. The theoretical recovery results based on restricted isometry property and $q$-ratio constrained minimal singular values are established. An algorithm that integrates the iteratively reweighted least squares algorithm and the difference of convex functions algorithm is given to approximately solve this non-convex problem. Numerical experiments are presented to illustrate our results.

Keywords: compressive sensing, nonconvex sparse recovery, iteratively reweighted least squares, difference of convex functions, $q$-ratio constrained minimal singular values

1. INTRODUCTION

Compressive sensing (CS) has attracted a great deal of interests since its advent [1, 2], see the monographs [3, 4] and the references therein for a comprehensive view. Basically, the goal of CS is to recover an unknown (approximately) sparse signal $x \in \mathbb{R}^N$ from the noisy underdetermined linear measurements

$$ y = Ax + e \in \mathbb{R}^m, $$

with $m \ll N$, $A \in \mathbb{R}^{m \times N}$ being the pre-given measurement matrix and $e \in \mathbb{R}^m$ being the noise vector. If the measurement matrix $A$ satisfies some kinds of incoherence conditions (e.g., mutual coherence condition [5, 6], restricted isometry property (RIP) [7, 8], null space property (NSP) [9, 10], or constrained minimal singular values (CMSV) [11, 12]), then stable (w.r.t. sparsity defect) and robust (w.r.t. measurement error) recovery results can be guaranteed by using the constrained $\ell_1$-minimization [13]:

$$ \min_{z \in \mathbb{R}^N} \|z\|_1 \quad \text{subject to} \quad \|Az - y\|_2 \leq \eta. $$

Here the $\ell_1$-minimization problem works as a convex relaxation of $\ell_0$-minimization problem, which is NP-hard to solve [14].

Meanwhile, non-convex recovery algorithms such as the $\ell_r$-minimization ($0 < r < 1$) have been proposed to enhance sparsity [15–20]. $\ell_r$-minimization enables one to reconstruct the sparse signal from fewer number of measurements compared to the convex $\ell_1$-minimization, although it is more challenging to solve because of its non-convexity. Fortunately, an iteratively reweighted least squares (IRLS) algorithm can be applied to approximately solve this non-convex problem in practice [21, 22].
As an extension of the $\ell_r$-minimization, we study in this paper the following weighted $\ell_r - \ell_1$ minimization problem for sparse signal recovery:

$$\min_{z \in \mathbb{R}^N} \|z\|_r^r - \alpha \|z\|_1^r \quad \text{subject to} \quad \|Az - y\|_2 \leq \eta, \tag{3}$$

where $y = Ax + e$ with $\|e\|_2 \leq \eta$, $0 \leq \alpha \leq 1$, and $0 < r \leq 1$. Throughout the paper, we assume that $\alpha \neq 1$ when $r = 1$. Obviously, it reduces to the traditional $\ell_r$-minimization problem when $\alpha = 0$. This hybrid norm model is inspired by the non-convex Lipschitz continuous $\ell_1 - \ell_2$ model (minimizing the difference of $\ell_1$ norm and $\ell_2$ norm) proposed in Lou et al. [23] and Yin et al. [24], which improves the $\ell_1$-minimization in a robust manner, especially for the highly coherent measurement matrices. Roughly speaking, the underlying logic of adopting these kinds of norm differences or the ratios of norms [25] comes from the fact that they can be viewed as sparsity measures, see the effective sparsity measure called $\ell_q$-ratio sparsity (including the ratio of $\ell_1$ norm and $\ell_q$ norm) defined later in Definition 2 of section 2.2. Other recent related literatures include [26–29], to name a few.

To illustrate these weighted $\ell_r - \ell_1$ norms ($\|\cdot\|_r^r - \alpha \|\cdot\|_1^r$), we present their corresponding contour plots in Figure 1. As is shown, different non-convex patterns arise while varying the difference weight $\alpha$ or the norm order $r$. And the level curves of weighted $\ell_r - \ell_1$ norms approach the x and y axes as the norm values get small, which reflects their ability to promote sparsity. In the present paper, we shall focus on both the theoretical aspects and the computational study for this non-convex sparse recovery method.

This paper is organized as follows. In section 2, we derive the theoretical performance bounds for the weighted $\ell_r - \ell_1$ minimization based on both $r$-RIP and $q$-ratio CMSV. In section 3, we give an algorithm to approximately solve the unconstrained version of the weighted $\ell_r - \ell_1$ minimization problem. Numerical experiments are provided in section 4. Section 5 concludes with a brief summary and an outlook on future extensions.

2. RECOVERY ANALYSIS

In this section, we establish the theoretical performance bounds for the reconstruction error of the weighted $\ell_r - \ell_1$ minimization problem, based on both $r$-RIP and $q$-ratio CMSV. Hereafter, we say a signal $x \in \mathbb{R}^N$ is $s$-sparse if $\|x\|_0 = \sum_{i=1}^{N} 1\{x_i \neq 0\} \leq s$, and denote by $x_S$ the vector that coincides with $x$ on the indices in $S \subseteq [N] := \{1, 2, \ldots, N\}$ and takes zero outside $S$.

2.1. $r$-RIP

We start with the definition of the $s$-th $r$-restricted isometry constant, which was introduced in Chartrand and Staneva [30].

Definition 1. ([30]) For integer $s > 0$ and $0 < r \leq 1$, the $s$-th $r$-restricted isometry constant (RIC) $\delta_s = \delta_s(A)$ of a matrix $A \in \mathbb{R}^{m \times N}$ is defined as the smallest $\delta \geq 0$ such that

$$\|(1 - \delta)\|_2 \leq \|Ax\|_r \leq (1 + \delta)\|x\|_2 \tag{4}$$

for all $s$-sparse vectors $x \in \mathbb{R}^N$.

Then, the $r$-RIP means that the $s$-th $r$-RIC $\delta_{s}$ is small for reasonably large $s$. In Chartrand and Staneva [30], the authors established the recovery analysis result for $\ell_r$-minimization problem based on this $r$-RIP. To extend this to the weighted $\ell_r - \ell_1$ minimization problem, the following lemma plays a crucial role.

Lemma 1. Suppose $x \in \mathbb{R}^N$, $0 \leq \alpha \leq 1$ and $0 < r \leq 1$, then we have

$$(N - \alpha N') \left( \min_{i \in [N]} |x_i| \right)^r \leq \|x\|_r^r - \alpha \|x\|_1^r \leq (N^{1-r} - \alpha)\|x\|_1^r. \tag{5}$$

In particular, when $S = \supp(x) \subseteq [N]$ and $|S| = s$, then

$$(s - \alpha s') \left( \min_{i \in S} |x_i| \right)^r \leq \|x\|_r^r - \alpha \|x\|_1^r \leq (s^{1-r} - \alpha)\|x\|_1^r. \tag{6}$$

Proof. The right hand side of (5) follows immediately from the norm inequality $\|x\|_r \leq N^{1/r-1}\|x\|_1$ for any $x \in \mathbb{R}^N$ and $0 < r \leq 1$. As for the left hand side, it holds trivially if $\min_{i \in [N]} |x_i| = 0$. When $\min_{i \in [N]} |x_i| \neq 0$, by dividing $(\min_{i \in [N]} |x_i|)^r$ on both sides, it is equivalent to show that

$$\sum_{j=1}^{N} \left( \frac{|x_j|}{\min_{i \in [N]} |x_i|} \right)^r - \alpha \left( \sum_{j=1}^{N} |x_j| / \min_{i \in [N]} |x_i| \right)^r \geq N - \alpha N'. \tag{7}$$

By denoting $a_j = \frac{|x_j|}{\min_{i \in [N]} |x_i|}$, we have $a_j \geq 1$ for any $1 \leq j \leq N$, and to show (7) it suffices to show

$$\sum_{j=1}^{N} a_j^r - \alpha \left( \sum_{j=1}^{N} a_j \right)^r \geq N - \alpha N'. \tag{8}$$

Assume the function $f(a_1, a_2, \ldots, a_N) = \sum_{j=1}^{N} a_j^r - \alpha \left( \sum_{j=1}^{N} a_j \right)^r$. Then, as a result of

$$\frac{\partial f}{\partial a_k} = ra_k^{r-1} - \alpha r \left( \sum_{j=1}^{N} a_j \right)^{r-1} > 0 \quad \text{for any} \quad 1 \leq k \leq N,$

we have $f(a_1, a_2, \ldots, a_N) \geq f(1, 1, \ldots, 1) = N - \alpha N'$. Thus, the left hand side of (5) holds and the proof is completed. (6) follows as we apply (5) to $x_S$.

Now, we are ready to present the $r$-RIP based bound for the $\ell_2$ norm of the reconstruction error.
Theorem 1. Let the $\ell_r$-error of best $s$-term approximation of $x$ be $\sigma_s(x) = \inf\{\|x - z\|_r, z \in \mathbb{R}^N\}$ is $s$-sparse. We assume that $a > 0$ is properly chosen so that $\hat{s}$ is as an integer. If

$$b = \frac{(as)^{1-\frac{s}{r}} - \alpha (as)}{s^{1-\frac{s}{r}} + \alpha s^{\frac{s}{r}}} > 1$$

and suppose the measurement matrix $A$ satisfies the condition

$$\delta_{as} + b\delta_{(a+1)s} < b - 1,$$

then any solution $\hat{x}$ to the minimization problem (3) obeys

$$\|\hat{x} - x\|_2 \leq C_1 m^{1/r - 1/2}\eta + C_2 (s^{1-\frac{s}{r}} + \alpha s^{\frac{s}{r}})^{-1/\tau} \sigma_s(x),$$

with

$$C_1 = \frac{2^{1/r(1 + \delta_{as})}}{(b - b\delta_{(a+1)s} - 1 - \delta_{as})^{1/r}},$$

and

$$C_2 = \frac{2^{2/r - 1}(1 + \delta_{as})^{1/r - 1 + (1 - \delta_{as})(1 + \delta_{as})^{1/r}}}{(b - b\delta_{(a+1)s} - 1 - \delta_{as})^{1/r}}.$$

Proof. We assume that $S$ is the index set that contains the largest $s$ absolute entries of $x$ so that $\sigma_s(x) = \|x_S\|_r$, and let $h = \hat{x} - x$. Then we have

$$\|x_S\|_r^r + \|x_{\bar{S}}\|_r^r \geq \|x_S\|_r^r - \alpha \|x\|_r^r$$

where $\bar{S} = S \cup S_S \cup \cdots$, where $S_1$ is the index set of $M = as$ largest absolute entries of $h$ in $S$, $S_2$ is the index set of $M$ largest absolute entries of $h$ in $(S \cup S_1)^c$, etc. And we denote $S_0 = S \cup S_1$. Then, by adopting Lemma 1, for each $i \in S_k, k \geq 2$,

$$|h_i| \leq \min_{j \in \hat{S}_{k-1}} |h_j| \Rightarrow |h_i|^r \leq \left( \min_{j \in \hat{S}_{k-1}} |h_j|^r \right) \leq \frac{\|h_{S_k-1}\|_r^r - \alpha \|h_{S_k-1}\|_1^r}{M - \alpha M^r}.$$
Therefore, with (11), it holds that

\[
\sum_{k \geq 2} \| \mathbf{h}_{S_k} \|^2_2 \leq \frac{\| \mathbf{h}_{S_1} \|^2\| - \mathbf{h}_{S_1} \|_1^{\prime}}{M^{1-\frac{s}{2}} - \alpha M^{\frac{s}{2}}}
\]

\[
\leq \frac{\| \mathbf{h}_{S_1} \|^2 + \alpha \| \mathbf{h}_{S_1} \|_1^{\prime} + 2 \| \mathbf{x}_{S_1} \|_r^{\prime}}{M^{1-\frac{s}{2}} - \alpha M^{\frac{s}{2}}}
\]

\[
\leq \frac{1}{b} \| \mathbf{h}_{S_1} \|_2^{\prime} + \frac{2(1 + \delta_M)(s^{1-\frac{s}{2}} + \alpha s^{\frac{s}{2}}) - 1}{b - b\delta_{M+s} - 1 - \delta_M} \| \mathbf{x}_{S_1} \|_r^{\prime} + \frac{2(s^{1-\frac{s}{2}} + \alpha s^{\frac{s}{2}}) - 1}{b} \| \mathbf{x}_{S_1} \|_r^{\prime}
\]

(16)

Meanwhile, according to the definition of r-RIC, we have

\[
\| \mathbf{A}\mathbf{h} \|_r^{\prime} = \| \mathbf{A}\mathbf{h}_{S_1} + \sum_{k \geq 2} \mathbf{A}\mathbf{h}_{S_k} \|_r^{\prime}
\]

\[
\geq \| \mathbf{A}\mathbf{h}_{S_1} \|_r^{\prime} - \| \sum_{k \geq 2} \mathbf{A}\mathbf{h}_{S_k} \|_r^{\prime}
\]

\[
\geq \| \mathbf{A}\mathbf{h}_{S_1} \|_r^{\prime} - \sum_{k \geq 2} \| \mathbf{A}\mathbf{h}_{S_k} \|_r^{\prime}
\]

\[
\geq (1 - \delta_{M+s})\| \mathbf{h}_{S_1} \|_2^{\prime} - (1 + \delta_M) \sum_{k \geq 2} \| \mathbf{h}_{S_k} \|_2^{\prime}.
\]

Thus by using (16), it follows that

\[
\| \mathbf{A}\mathbf{h} \|_r^{\prime} \geq (1 - \delta_{M+s})\| \mathbf{h}_{S_1} \|_2^{\prime} - (1 + \delta_M) \cdot \frac{(s^{1-\frac{s}{2}} + \alpha s^{\frac{s}{2}})\| \mathbf{h}_{S_1} \|_2^{\prime} + 2 \| \mathbf{x}_{S_1} \|_r^{\prime}}{M^{1-\frac{s}{2}} - \alpha M^{\frac{s}{2}}}
\]

\[
= \left(1 - \delta_{M+s} - \frac{1 + \delta_M}{b}\right)\| \mathbf{h}_{S_1} \|_2^{\prime} - \frac{2(1 + \delta_M)(s^{1-\frac{s}{2}} + \alpha s^{\frac{s}{2}}) - 1}{b - b\delta_{M+s} - 1 - \delta_M} \| \mathbf{x}_{S_1} \|_r^{\prime},
\]

where \( b = M^{1-\frac{s}{2}} - \alpha M^{\frac{s}{2}} \). Therefore, if \( \delta_M + b\delta_{M+s} < b - 1 \), then it yields that

\[
\| \mathbf{h}_{S_1} \|_2^{\prime} \leq \frac{b}{b - b\delta_{M+s} - 1 - \delta_M} \| \mathbf{A}\mathbf{h} \|_r^{\prime}
\]

\[
\leq \frac{b}{b - b\delta_{M+s} - 1 - \delta_M} \| \mathbf{A}\mathbf{h}_{S_1} \|_r^{\prime} + \frac{2(1 + \delta_M)(s^{1-\frac{s}{2}} + \alpha s^{\frac{s}{2}}) - 1}{b - b\delta_{M+s} - 1 - \delta_M} \| \mathbf{x}_{S_1} \|_r^{\prime}
\]

(17)

On the other hand,

\[
\left( \sum_{k \geq 2} \| \mathbf{h}_{S_k} \|_2^{\prime} \right)^{\prime} \leq \sum_{k \geq 2} \| \mathbf{h}_{S_k} \|_2^{\prime}
\]

\[
\leq \frac{(s^{1-\frac{s}{2}} + \alpha s^{\frac{s}{2}})\| \mathbf{h}_{S_1} \|_2^{\prime} + 2 \| \mathbf{x}_{S_1} \|_r^{\prime}}{M^{1-\frac{s}{2}} - \alpha M^{\frac{s}{2}}}
\]

\[
= \frac{1}{b} \frac{b}{b - b\delta_{M+s} - 1 - \delta_M} \| \mathbf{A}\mathbf{h} \|_r^{\prime}
\]

\[
\leq \frac{1}{b} \frac{b}{b - b\delta_{M+s} - 1 - \delta_M} \| \mathbf{A}\mathbf{h}_{S_1} \|_r^{\prime} + \frac{2(1 + \delta_M)(s^{1-\frac{s}{2}} + \alpha s^{\frac{s}{2}}) - 1}{b - b\delta_{M+s} - 1 - \delta_M} \| \mathbf{x}_{S_1} \|_r^{\prime}
\]

(18)

Since \( (\mathbf{v}_1 + \mathbf{v}_2)^{1/r} \leq 2^{1/r - 1}(\mathbf{v}_1 + \mathbf{v}_2) \) for any \( \mathbf{v}_1, \mathbf{v}_2 \geq 0 \), combining (17) and (18) gives

\[
\| \mathbf{h} \|_2 \leq \| \mathbf{h}_{S_1} \|_2 + \sum_{k \geq 2} \| \mathbf{h}_{S_k} \|_2
\]

\[
\leq 2^{1/r - 1} \left( \frac{2b^{1/r}m^{1/r - 1/2} \eta}{(b - b\delta_{M+s} - 1 - \delta_M)^{1/r}} + \frac{2^{1/r}(1 + \delta_M)^{1/r}(s^{1-\frac{s}{2}} + \alpha s^{\frac{s}{2}})^{-1/r}}{(b - b\delta_{M+s} - 1 - \delta_M)^{1/r}} \| \mathbf{x}_{S_1} \|_r^{\prime} \right)
\]

\[
+ \frac{2^{1/r - 1} \left( 2m^{1/r - 1/2} \eta \right)}{(b - b\delta_{M+s} - 1 - \delta_M)^{1/r}} \| \mathbf{x}_{S_1} \|_r^{\prime}
\]

\[
= \frac{2^{1/r}m^{1/r - 1/2}(1 + b^{1/r})}{(b - b\delta_{(a+1)^r} - 1 - \delta_{a^{1/r}})^{1/r}} + \frac{2^{2/r - 1} \left[ (1 + \delta_{a^{1/r}} + 1 - \delta_{(a+1)^r})^{1/r} \right]}{(b - b\delta_{(a+1)^r} - 1 - \delta_{a^{1/r}})^{1/r}} \times (s^{1-\frac{s}{2}} + \alpha s^{\frac{s}{2}})^{-1/r} \| \mathbf{x}_{S_1} \|_r^{\prime}
\]

\[
\leq C_1 m^{1/r - 1/2} \eta + C_2 (s^{1-\frac{s}{2}} + \alpha s^{\frac{s}{2}})^{-1/r} \| \mathbf{x}_{S_1} \|_r^{\prime}. \]

The proof is completed.

Based on this theorem, we can obtain the following corollary by assuming that the original signal \( \mathbf{x} \) is \( s \)-sparse \( (\sigma_s(x) = 0) \) and the measurement vector is noise free \( (\varepsilon = 0 \text{ and } \eta = 0) \), which acts as a natural generalization of Theorem 2.4 in Chartrand and Staneva [30] from the case \( \alpha = 0 \) to any \( \alpha \in [0, 1] \).

**Corollary 1.** For any \( s \)-sparse signal \( \mathbf{x} \), if the conditions in Theorem 1 hold, then the unique solution of (3) with \( \eta = 0 \) is exactly \( \mathbf{x} \).

**Remarks.** Observe that r-RIP based condition for exact sparse recovery given in Chartrand and Staneva [30] reads

\[
\delta_{as} < a^{1-\frac{s}{2}}(1 - \delta_{(a+1)r}) - 1,
\]

while ours goes to

\[
\delta_{as} < b(1 - \delta_{(a+1)b}) - 1
\]
with \( b = \frac{(a_0)\alpha^{\frac{1}{q}}}{\alpha^{\frac{1}{\pi}} + \alpha^{\frac{1}{q}}} < a^{1-\frac{1}{\pi}} \) when \( \alpha \in (0, 1] \). Thus, the sufficient condition established here is slightly stronger than that for the traditional \( \ell_r \)-minimization in Chartrand and Staneva [30] if \( \alpha \in (0, 1] \).

### 2.2. q-Ratio CMSV

Before the discussion of q-ratio CMSV, we start with presenting the definition of q-ratio sparsity as a kind of effective sparsity measure. We list the detailed statement here for the sake of completeness.

**Definition 2.** ([12, 31, 32]) For any non-zero \( z \in \mathbb{R}^N \) and non-negative \( q \notin \{0, 1, \infty\} \), the q-ratio sparsity level of \( z \) is defined as

\[
s_q(z) = \left( \frac{\|z\|_1}{\|z\|_q} \right)^{\frac{q}{1-q}}.
\]

The cases of \( q \in \{0, 1, \infty\} \) are evaluated as limits:

- \( s_0(z) = \lim_{q \to 0} s_q(z) = \|z\|_0 \frac{s_\infty(z)}{s_\infty(z)} \), where \( s_\infty(z) \) is the total \( \ell_\infty \) norm, and
- \( s_1(z) = \lim_{q \to 1} s_q(z) = \exp(H_1(\pi(z))), \) where \( \pi(z) \in \mathbb{R}^N \) with entries \( \pi_i(z) = |z_i|/\|z\|_1 \) and \( H_1(\pi(z)) = -\sum_i \pi_i(z) \log \pi_i(z). \)

We are able to establish the performance bounds for both the \( \ell_q \) norm and \( \ell_r \) norm of the reconstruction error via a recently developed computable incoherence measure of the measurement matrix, called q-ratio CMSV. Its definition is given as follows.

**Definition 3.** ([12, 32]) For any real number \( s \in [1, N], \ q \in (1, \infty], \) and matrix \( A \in \mathbb{R}^{m \times N} \), the q-ratio constrained minimal singular value (CMSV) of \( A \) is defined as

\[
\rho_{q,s}(A) = \min_{\|z\|_q \leq s} \frac{\|Az\|_2}{\|z\|_q}.
\]

Then, when the signal is exactly sparse, we have the following q-ratio CMSV based sufficient condition for valid upper bounds of the reconstruction error, which are much more concise to obtain than the \( r \)-RIP based ones.

**Theorem 2.** For any \( 1 < q \leq \infty, \ 0 \leq \alpha \leq 1, \) and \( 0 < r \leq 1, \) if the signal \( x \) is \( s \)-sparse and the measurement matrix \( A \) satisfies the condition

\[
\rho_{q, s}(A) > 0,
\]

then any solution \( \hat{x} \) to the minimization problem (3) obeys

\[
\|\hat{x} - x\|_q \leq \frac{2\eta}{\rho_{q, s}(A)}^{\alpha^{\frac{1}{q}} - \frac{1\alpha}{q}}(A),
\]

\[
\|\hat{x} - x\|_r \leq \left( \frac{2^{r+1}}{1 - \alpha} \right)^{\frac{1}{r}} \cdot \frac{s_1^{1/r-1/q\eta}}{\rho_{q, s}(A)^{\alpha^{\frac{1}{q}} - \frac{1\alpha}{q}}(A)}.
\]

**Proof.** Suppose the support of \( x \) to be \( S \) with \( |S| \leq s \) and \( h = \hat{x} - x \), then, based on (11), we have

\[
\|h\|_r \leq \|h\|_r - \alpha \|h\|_r \leq \|h\|_r + \alpha \|h\|_r,
\]

\[
\|h\|_r \leq \|h\|_r - \alpha \|h\|_r \leq \|h\|_r + \alpha \|h\|_r,
\]

Hence, for any \( 1 < q \leq \infty, \) holds that

\[
\|h\|_r - \alpha \|h\|_r \leq \|h\|_r + \alpha \|h\|_r.
\]

Then since \( (1 - \alpha) \|h\|_r \leq \|h\|_r - \alpha \|h\|_r, \) it implies that \( (1 - \alpha) \|h\|_r \leq 2s_1^{1/r-1/q}\|h\|_q. \) As a consequence,

\[
s_q(h) = \left( \frac{\|h\|_1}{\|h\|_q} \right)^{\frac{q}{1-q}} \leq \left( \frac{2s_1^{1/r-1/q}}{1 - \alpha} \right)^{\frac{q}{1-q}}
\]

\[
= \left( \frac{2}{1 - \alpha} \right)^{\frac{q}{1-q}} \cdot \frac{s_1^{1/r-1/q\eta}}{(\frac{1}{r})^{\alpha^{\frac{1}{q}} - \frac{1\alpha}{q}}(A)}.
\]

Therefore, according to the definition of q-ratio CMSV the condition (22), and the fact that \( \|Ah\|_2 \leq 2\eta \) [see (12)], we can obtain that

\[
\rho_{q, s}(A) \leq \frac{\|Ah\|_2}{\|h\|_q} \Rightarrow \|h\|_q \leq \rho_{q, s}(A) \leq \frac{\|Ah\|_2}{\|h\|_q} \leq \rho_{q, s}(A) \leq \frac{\|Ah\|_2}{\|h\|_q} \leq \frac{2\eta}{\rho_{q, s}(A)}^{\alpha^{\frac{1}{q}} - \frac{1\alpha}{q}}(A).
\]

which completes the proof of (23). In addition, \( (1 - \alpha) \|h\|_r \leq 2s_1^{1/r-1/q}\|h\|_q \) yields

\[
\|h\|_r \leq \left( \frac{2}{1 - \alpha} \right)^{\frac{1}{r}} \cdot \frac{s_1^{1/r-1/q\eta}}{(\frac{1}{r})^{\alpha^{\frac{1}{q}} - \frac{1\alpha}{q}}(A)}.
\]

Therefore, (24) holds and the proof is completed.

**Remarks.** Note that the results (11) and (12) in Theorem 1 of Zhou and Yu [12] correspond to the special case of \( \alpha = 0 \) and \( r = 1 \) in this result. As a by-product of this theorem, we have that the perfect recovery can be guaranteed for any s-sparse signal \( x \) via (3) with \( \eta = 0, \) if there exists some \( q \in (1, \infty] \) such that the q-ratio CMSV of the measurement matrix \( A \) fulfills \( \rho_{q, s}(A) > 0. \) As studied in Zhou and Yu [12, 32], this kind of q-ratio CMSV based sufficient conditions holds with high probability for subgaussian and a class of structured random matrices as long as the number of measurements is reasonably large.

Next, we extend the result to the case that \( x \) is compressible (i.e., not exactly sparse but can be well-approximated by an exactly sparse signal).
Theorem 3. For any $1 < q \leq \infty$, $0 \leq \alpha \leq 1$ and $0 < r \leq 1$, if the measurement matrix $A$ satisfies the condition
\[
\rho_{\frac{q}{2}}\left(\frac{4}{\rho_{\frac{q}{2}}} \frac{q^{-r}}{\rho_{\frac{q}{2}}} \frac{q^{-r}}{\rho_{\frac{q}{2}}}(A)\right) > 0, \tag{29}
\]
then any solution $\hat{x}$ to the minimization problem (3) fulfills
\[
\|\hat{x} - x\|_q \leq \frac{2\eta}{\rho_{\frac{q}{2}}\left(\frac{4}{\rho_{\frac{q}{2}}} \frac{q^{-r}}{\rho_{\frac{q}{2}}} \frac{q^{-r}}{\rho_{\frac{q}{2}}}(A)\right)} + s^{1/q-1/r} \sigma_s(x)_r, \tag{30}
\]
\[
\|\hat{x} - x\|_r \leq \frac{4}{1 - \alpha} \frac{s^{1/r-1/q} \eta}{\rho_{\frac{q}{2}}\left(\frac{4}{\rho_{\frac{q}{2}}} \frac{q^{-r}}{\rho_{\frac{q}{2}}} \frac{q^{-r}}{\rho_{\frac{q}{2}}}(A)\right)} + \left(\frac{4}{1 - \alpha}\right)^{1/r} \sigma_s(x)_r. \tag{31}
\]

Proof. We assume that $S$ is the index set that contains the largest $s$ absolute entries of $x$ so that $\sigma_s(x)_r = \|x_{S^c}\|_r$, and let $h = \hat{x} - x$. Then we still have (11), that is,
\[
\|h_{S^c}\|_r^r - \alpha \|h_{S^c}\|_r^r \leq \|h_S\|_r^r + \alpha \|h_{S^c}\|_r^r + 2\|x_{S^c}\|_r^r. \tag{32}
\]

As a result,
\[
(1 - \alpha)\|h\|_r^r \leq \|h\|_r^r - \alpha \|h\|_r^r \leq \|h_S\|_r^r + \|h_S\|_r^r - \alpha \|h_S\|_r^r - \alpha \|h_{S^c}\|_r^r \leq 2\|h_S\|_r^r + 2\|x_{S^c}\|_r^r \leq 2s^{1/r-1/q} \|h\|_q^r + 2\|x_{S^c}\|_r^r \tag{33}
\]
holds for any $1 < q \leq \infty$, $0 \leq \alpha \leq 1$ and $0 < r \leq 1$. To prove (30), we assume $h \neq 0$ and $\|h\|_q > \frac{2\eta}{\rho_{\frac{q}{2}}\left(\frac{4}{\rho_{\frac{q}{2}}} \frac{q^{-r}}{\rho_{\frac{q}{2}}} \frac{q^{-r}}{\rho_{\frac{q}{2}}}(A)\right)}$, otherwise it holds trivially. Then
\[
\|h\|_q > \frac{\|A^n v\|_2}{\rho_{\frac{q}{2}}\left(\frac{4}{\rho_{\frac{q}{2}}} \frac{q^{-r}}{\rho_{\frac{q}{2}}} \frac{q^{-r}}{\rho_{\frac{q}{2}}}(A)\right)} \Rightarrow s_q(h) > \left(\frac{4}{1 - \alpha}\right)^{\frac{q}{2}} \frac{s^{1/r-1/q} \rho_{\frac{q}{2}}\left(\frac{4}{\rho_{\frac{q}{2}}} \frac{q^{-r}}{\rho_{\frac{q}{2}}} \frac{q^{-r}}{\rho_{\frac{q}{2}}}(A)\right)}{\rho_{\frac{q}{2}}\left(\frac{4}{\rho_{\frac{q}{2}}} \frac{q^{-r}}{\rho_{\frac{q}{2}}} \frac{q^{-r}}{\rho_{\frac{q}{2}}}(A)\right)} \Rightarrow \|h_S\|_r > \frac{4}{1 - \alpha} s^{1/r-1/q} \|h\|_q^r,
\]
which implies that
\[
(1 - \alpha)\|h\|_r^r \geq (1 - \alpha)\|h\|_r^r > 4s^{1/r-1/q} \|h\|_q^r.
\]
Then combining with (33), it yields that
\[
\|h\|_q \leq (s^{r/q-1/r})^{1/r} \|x_{S^c}\|_r = s^{1/q-1/r} \|x_{S^c}\|_r = s^{1/q-1/r} \sigma_s(x)_r. \tag{34}
\]

Therefore, we have
\[
\|h\|_q \leq \frac{2\eta}{\rho_{\frac{q}{2}}\left(\frac{4}{\rho_{\frac{q}{2}}} \frac{q^{-r}}{\rho_{\frac{q}{2}}} \frac{q^{-r}}{\rho_{\frac{q}{2}}}(A)\right)} + s^{1/q-1/r} \sigma_s(x)_r, \tag{35}
\]
which completes the proof of (30).

Moreover, by using (33) and the inequality $(v_1^r + v_2^r)^{1/r} \leq 2^{1/r-1}(v_1 + v_2)$ for any $v_1, v_2 \geq 0$, we obtain that
\[
\|h\|_r \leq \left(\frac{1}{1 - \alpha}\right)^{1/r} \left(2s^{1/r-1/q} \|h\|_q^r + 2\|x_{S^c}\|_r^r\right) \leq \left(\frac{1}{1 - \alpha}\right)^{1/r} 2s^{1/r-1/q} \|h\|_q + \|x_{S^c}\|_r^r \leq \left(\frac{1}{1 - \alpha}\right)^{1/r} \left(s^{1/r-1/q} \|h\|_q + 2s^{1/r-1/q} \|x_{S^c}\|_r^r\right) \leq \left(\frac{4}{1 - \alpha}\right)^{1/r} \left(s^{1/r-1/q} \|h\|_q + 2s^{1/r-1/q} \|x_{S^c}\|_r^r\right) \leq \left(\frac{4}{1 - \alpha}\right)^{1/r} \left(s^{1/r-1/q} \|h\|_q + 2s^{1/r-1/q} \|x_{S^c}\|_r^r\right) \leq \left(\frac{4}{1 - \alpha}\right)^{1/r} \sigma_s(x)_r. \tag{36}
\]

Hence, (31) holds and the proof is completed.

Remarks. When we select $\alpha = 0$ and $r = 1$, our results reduce to the corresponding results for the $\ell_1$-minimization or Basis Pursuit in Theorem 2 of Zhou and Yu [12]. In general, the sufficient condition provided here and that in Theorem 2 are slightly stronger than those established for the $\ell_1$-minimization in Zhou and Yu [12], noticing that $\left(\frac{2}{1 - \alpha}\right)^{\frac{q}{2}} > \frac{2\eta}{\rho_{\frac{q}{2}}\left(\frac{4}{\rho_{\frac{q}{2}}} \frac{q^{-r}}{\rho_{\frac{q}{2}}} \frac{q^{-r}}{\rho_{\frac{q}{2}}}(A)\right)}$ and $\left(\frac{4}{1 - \alpha}\right)^{\frac{q}{2}} > \frac{2\eta}{\rho_{\frac{q}{2}}\left(\frac{4}{\rho_{\frac{q}{2}}} \frac{q^{-r}}{\rho_{\frac{q}{2}}} \frac{q^{-r}}{\rho_{\frac{q}{2}}}(A)\right)}$ for any $1 < q \leq \infty$, $0 \leq \alpha \leq 1$, and $0 < r \leq 1$. This is caused by the fact that the technical inequalities used like (25) and (32) are far from tight. And this is also the case in the $r$-RIP based analysis. In fact, both $r$-RIP and $q$-ratio CMSV based conditions are loose. The discussion on much tighter sufficient conditions such as the NSP based conditions investigated in Tran and Webster [33], is left for future work.

3. ALGORITHM

In this section, we discuss the computational approach for the unconstrained version of (3), i.e.,
\[
\min_{x \in \mathbb{R}^N} \frac{1}{2} \|Ax - y\|_2^2 + \lambda\|x\|_p^p - \alpha\|x\|_1^1, \tag{37}
\]
with $\lambda > 0$ being the regularizer parameter.

We integrate the iteratively reweighted least squares (IRLS) algorithm [21, 22] and the difference of convex functions algorithm (DCA) [34, 35] to solve this problem. In the outer loop, we use the IRLS to approximate the term $\|x\|_r^r$ and use an iteratively reweighted $\ell_1$ norm to approximate $\|x\|_1^1$. Specifically, we begin with $x_0^1 = \arg \min_{x \in \mathbb{R}^N} \|y - Ax\|_2^2$ and $\varepsilon_0 = 1$, for $n = 0, 1, \cdots$,
\[
x_n^{n+1} = \arg \min_{x \in \mathbb{R}^N} \frac{1}{2} \|Ax - y\|_2^2 + \lambda\|W_n x\|_2^2 - \alpha \lambda y^p \|x\|_1^1, \tag{38}
\]
where $W_n = \text{diag}((\|x_n^p\|_2^2 + 3\varepsilon_n)^{r/4-1/2})$ and $y^p = \|x_n^p\|_1^{r-1}$. We let $\varepsilon_n = \varepsilon_n / 10$ if the error $\|x_n^{n+1} - x_n^n\|_2^2 < 3\varepsilon_n / 100$. The algorithm is stopped when $\varepsilon_n < 10^{-8}$ for some $n$. 


As for the inner loop used to solve (38), we view it as a minimization problem of a difference of two convex functions, that is, the objective function 

\[ F(x) = \left( \frac{1}{2} \| Ax - y \|_2^2 + \lambda \| W^n x \|_2^2 \right) - \alpha \lambda \nu^n \| x \|_1 = : G(x) - H(x). \]

We start with \( x^{n+1,0} = 0 \). For \( k = 0, 1, 2, \ldots \), in the \( k + 1 \) step, by linearizing \( H(x) \) with the approximation \( H(x^{n+1,k}) + \langle y^{n+1,k}, x - x^{n+1,k} \rangle \) where \( y^{n+1,k} \in \partial H(x^{n+1,k}) \), i.e. \( y^{n+1,k} \) is a subgradient of \( H(x) \) at \( x^{n+1,k} \). Then we have

\[
\begin{align*}
x^{n+1,k+1} &= \arg \min_{x \in \mathbb{R}^N} \frac{1}{2} \| Ax - y \|_2^2 + \lambda \| W^n x \|_2^2 \\
&\quad - (\alpha \lambda \nu^n \| x^{n+1,k} \|_1 + (\alpha \lambda \nu^n \text{sign}(x^{n+1,k}), x - x^{n+1,k})) \\
&= \arg \min_{x \in \mathbb{R}^N} \frac{1}{2} \| Ax - y \|_2^2 + \lambda \| W^n x \|_2^2 - (\alpha \lambda \nu^n \text{sign}(x^{n+1,k}), x) \\
&= (A^T A + 2 \lambda (W^n)^T W^n)^{-1} A^T y + \alpha \lambda \nu^n \text{sign}(x^{n+1,k}),
\end{align*}
\]

where \( \text{sign}(\cdot) \) is the sign function. The termination criterion for the inner loop is set to be

\[
\frac{\| x^{n+1,k+1} - x^{n+1,k} \|_2}{\max(\| x^{n+1,k} \|_2, 1)} < \delta
\]

for some given parameter tolerance parameter \( \delta > 0 \). Basically, this algorithm can be regarded as a generalized version of IRLS algorithm. Obviously, when \( \alpha = 0 \), it exactly reduces to the traditional IRLS algorithm used for solving the \( \ell_1 \)-minimization problem.

4. NUMERICAL EXPERIMENTS

In this section, some numerical experiments on the proposed algorithm in section 3 are conducted to illustrate the performance of the weighted \( \ell_r - \ell_1 \) minimization in simulated sparse signal recovery.

4.1. Successful Recovery

First, we focus on the weighted \( \ell_r - \ell_1 \) minimization itself. In this set of experiments, the \( s \)-sparse signal \( x \) is of length \( N = 256 \), which is generated by choosing \( s \) entries uniformly at random, and then choosing the non-zero values from the standard normal distribution for these \( s \) entries. The underdetermined linear measurements \( y = Ax + e \in \mathbb{R}^m \), where \( A \in \mathbb{R}^{m \times N} \) is a standard Gaussian random matrix and the entries of the noise vector \( \{ e_i, i = 1, 2, \ldots, m \} \) is \( \mathcal{N}(0, \sigma^2) \). Here we fix the number of measurements \( m = 64 \) and select a sequence of \( s \) as 10, 12, \ldots, 36. We run the experiments for both noiseless and noisy cases. In all the experiments, we let the tolerance parameter \( \delta = 10^{-3} \), and all the results are averaged over 100 repetitions.

In the noiseless case, i.e., \( \sigma = 0 \), we set \( \lambda = 10^{-6} \). In Figure 2, we show the results of successful recovery rate for different \( \alpha \) (i.e., \( \alpha = 0.0, 0.2, 0.5, 0.8, 1 \)) while fixing \( r \) but varying the sparsity level \( s \). We view it as a successful recovery if \( \| \hat{x} - x \|_2/\| x \|_2 < 10^{-3} \). We do the experiments for \( r = 0.3 \) and \( r = 0.7 \), respectively. As we can see, when \( r \) is fixed, the influence of the weight \( \alpha \) is negligible, especially in the case that \( r \) is relatively small. But the performance does improve in some scenarios when a proper weight \( \alpha \) is used. However, the problem of adaptively selecting the optimal \( \alpha \) seems to be challenging and is left for future work. In addition, we present the reconstruction performances for different \( r \) (i.e., \( r = 0.01, 0.2, 0.5, 0.8, 1 \)) while the weight \( \alpha \) is fixed to be 0.2 and 0.8 in Figure 3. Note that small \( r \) is favored when the weight \( \alpha \) is fixed. And a non-convex recovery with \( 0 < r < 1 \) performs much better than the convex case \((r = 1)\).

Next, we consider the noisy case, that is \( \sigma = 0.01 \). We set \( \lambda = 10^{-4} \). And we evaluate the recovery performance by the signal to noise ratio (SNR), which is given by

\[
\text{SNR} = 20 \log_{10} \left( \frac{\| x \|_2}{\| x - \hat{x} \|_2} \right).
\]
As shown in Figures 4, 5, the findings aforementioned can still be seen here.

4.2. Algorithm Comparisons

Second, we compare the weighted $\ell_{r} - \ell_{1}$ minimization with some well-known algorithms. The following state-of-the-art recovery algorithms are operated:

- ADMM-Lasso, see Boyd et al. [36].
- CoSaMP, see Needell and Tropp [37].
- Iterative Hard Thresholding (IHT), see Blumensath and Davies [38].
- $\ell_{1} - \ell_{2}$ minimization, see Yin et al. [24].

The tuning parameters used for these algorithms are the same as those adopted in section 5.2 of Yin et al. [24]. Specifically, for ADMM-Lasso, we choose $\lambda = 10^{-6}$, $\beta = 1$, $\rho = 10^{-5}$, $\varepsilon_{\text{abs}} = 10^{-7}$, $\varepsilon_{\text{rel}} = 10^{-5}$, and the maximum number of iterations $\text{maxiter} = 5,000$. For CoSaMP, $\text{maxiter} = 50$ and the tolerance is set to be $10^{-8}$. The tolerance for IHT is $10^{-12}$. For $\ell_{1} - \ell_{2}$ minimization, we choose the parameters as $\varepsilon_{\text{abs}} = 10^{-7}$, $\varepsilon_{\text{rel}} = 10^{-5}$, $\varepsilon = 10^{-2}$, $\text{MAXoit} = 10$, and $\text{MAXit} = 500$. For our weighted $\ell_{r} - \ell_{1}$ minimization, we choose $\lambda = 10^{-6}$, $r = 0.5$ but with two different weights $\alpha = 0$ (denoted as $\ell_{0.5}$) and $\alpha = 1$ (denoted as $\ell_{0.5} - \ell_{1}$).

We only consider the exactly sparse signal recovery in the noiseless case, and conduct the experiments under the same settings as in section 4.1. We present the successful
recovery rates for different reconstruction algorithms while varying the sparsity level $s$ in Figure 6. It can be observed that both $\ell_{0.5}$ and $\ell_{0.5} - \ell_1$ outperform over other algorithms, although their own performances are almost the same.

5. CONCLUSION

In this paper, we studied a new non-convex recovery method, developed as minimizing a weighted difference of $\ell_r$ ($0 < r \leq 1$) norm and $\ell_1$ norm. We established the performance bounds for this problem based on both $r$-RIP and $q$-ratio CMSV. An algorithm was proposed to approximately solve the non-convex problem. Numerical experiments show that the proposed algorithm provides superior performance compared to the existing algorithms such as ADMM-Lasso, CoSaMP, IHT and $\ell_1 - \ell_2$ minimization.

Besides, there are some open problems left for future work. One is the convergence study of the proposed algorithm in section 3. Another one is the generalization of this 1-D non-convex version to 2-D non-convex total variation minimization as done in Lou et al. [39] and the exploration of its application to medical imaging. Moreover, analogous to the non-convex
block-sparse compressive sensing studied in Wang et al. [40], the study of the following non-convex block-sparse recovery minimization problem:

$$\min_{z \in \mathbb{R}^N} \|z\|_{2,r}^r - \alpha \|z\|_{2,1} \quad \text{subject to} \quad \|Az - y\|_2 \leq \eta, \quad (39)$$

where $\|z\|_{2,r} = (\sum_{i=1}^p \|z[i]\|_2^r)^{1/r}$ with $z[i]$ denoting the $i$-th block of $z$, $0 \leq \alpha \leq 1$, and $0 < r \leq 1$, is also an interesting topic for further investigation.

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**AUTHOR CONTRIBUTIONS**

ZZ contributed to the initial idea and wrote the first draft. JY provided critical feedback and helped to revise the manuscript.

**FUNDING**

This work is supported by the Swedish Research Council grant (Reg.No. 340-2013-5342).
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