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Weighted ℓ_p-Minimization for Sparse Signal Recovery under Arbitrary Support Prior

Yueqi Ge[1], Wengu Chen[2,*], Huanmin Ge[3] and Yaling Li[4]

[1] *Liwan Primary School, Shenzhen, Guangdong 518000, China*
[2] *Institute of Applied Physics and Computational Mathematics, Beijing 100088, China*
[3] *The Sports Engineering College, Beijing Sport University, Beijing 100088, China*
[4] *Department of Mathematics, Zhejiang University of Science and Technology, Hangzhou, Zhejiang 310023, China*

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Dedicated to Prof. Shanzhen Lu with admiration on the occasion of his 80th birthday

Abstract. Weighted ℓ_p $(0 < p \leq 1)$ minimization has been extensively studied as an effective way to reconstruct a sparse signal from compressively sampled measurements when some prior support information of the signal is available. In this paper, we consider the recovery guarantees of k-sparse signals via the weighted ℓ_p $(0 < p \leq 1)$ minimization when arbitrarily many support priors are given. Our analysis enables an extension to existing works that assume only a single support prior is used.

Key Words: Adaptive recovery, compressed sensing, weighted ℓ_p minimization, sparse representation, restricted isometry property.

AMS Subject Classifications: 90C26, 90C30, 94A20

1 Introduction

Compressed sensing [2, 5] is a new data acquisition paradigm, which reliably recovers a high dimensional sparse signal $\boldsymbol{x} \in \mathbb{R}^n$ (a signal is called k-sparse if the number of its nonzero entries has at most $k \ll n$) from significantly fewer linear observations

$$\boldsymbol{y} = \boldsymbol{\Phi}\boldsymbol{x} + \boldsymbol{e}, \tag{1.1}$$

where $\boldsymbol{\Phi} \in \mathbb{R}^{m\times n}$ is a measurement matrix and $\boldsymbol{e} \in \mathbb{R}^m$ denotes additive noise that satisfies $\|\boldsymbol{e}\|_2 \leq \epsilon$ for some known $\epsilon \geq 0$. Compressed sensing is nonadaptive because the measurement matrix $\boldsymbol{\Phi}$ does not depend on the signal being measured. But, some

*Corresponding author. *Email addresses:* `geyueqi123@163.com` (Y. Ge), `chenwg@iapcm.ac.cn` (W. Chen), `gehuanmin@163.com` (H. Ge), `leeyaling@126.com` (Y. Li)

prior information of the signal $\boldsymbol{x}$ may be included in the estimates of the support of $\boldsymbol{x}$ or some estimates of largest coefficients of $\boldsymbol{x}$ in some settings. For example, video and audio signals exhibit strong correlation over temporal frames, which can be used to estimate a portion of the support based on previously decoded frames (see [6]). Therefore, the recovery of the signal $\boldsymbol{x}$ incorporating prior support information has received much attention including the weighted ℓ_1-minimization [3, 4, 6, 14, 16, 17, 19], the weighted ℓ_p $(0 < p < 1)$-minimization [10, 11, 13, 18] and the greedy algorithm with partial support information [7, 12, 15].

This paper considers the recovery of the signal $\boldsymbol{x}$ from (1.1) and is devoted to new RIP bounds for the exact and stable recovery of sparse signals with arbitrary many support priors via the weighted ℓ_p-minimization:

$$\min_{\boldsymbol{x}\in\mathbb{R}^n} \|\boldsymbol{x}\|_{p,\mathbf{w}}^p \quad \text{subject to} \quad \|\boldsymbol{\Phi}\boldsymbol{x}-\boldsymbol{y}\|_2 \le \varepsilon, \tag{1.2}$$

where $\mathbf{w} \in [0,1]^n$ is a weight vector and

$$\|\boldsymbol{x}\|_{p,\mathbf{w}} = \Big(\sum_{i=1}^n \mathrm{w}_i |x_i|^p\Big)^{\frac{1}{p}}.$$

The main idea inherited in the weighted ℓ_p $(0 < p \le 1)$-minimization is to make the entries of $\boldsymbol{x}$, which are "expected" to be large, be penalized less in the weighted objective function in (1.2) by the effect of the weight $\mathbf{w}$.

As $p = 1$, the method (1.2) reduces to the weighted ℓ_1-minimization:

$$\min_{\boldsymbol{x}\in\mathbb{R}^n} \|\boldsymbol{x}\|_{1,\mathbf{w}} \quad \text{subject to} \quad \|\boldsymbol{\Phi}\boldsymbol{x}-\boldsymbol{y}\|_2 \le \varepsilon. \tag{1.3}$$

The rest of the paper is organized as follows. In Section 2, we recall a recently established RIP bound for signal recovery by virtue of the weighted ℓ_p-minimization with a single weight. In Section 3, we respectively present sufficient conditions for the recovery of sparse signals by weighted ℓ_p-minimization with non-uniform weights in both the noiseless and ℓ_2 bounded noise. Section 4 is devoted to the proofs of the main results.

2 Weighted ℓ_p-minimization with a single weight

Let $\widetilde{T} \subseteq [n] = \{1, 2, \cdots, n\}$ be a known single support estimate of $\boldsymbol{x}$. The weight vector $\mathbf{w}$ in this case is taken by

$$\mathrm{w}_i = \begin{cases} \omega, & i \in \widetilde{T}, \\ 1, & i \in \widetilde{T}^c, \end{cases} \tag{2.1}$$

for some fixed $\omega \in [0,1]$ and $i \in [n]$.

The restricted isometry property (RIP) is one of the main tools used to evaluate the recovery performance via a variety of efficient algorithms. The RIP notion introduced by Candès et al. in [2], is the most widely used framework in compressed sensing.

Definition 2.1. *For a matrix* $\mathbf{\Phi} \in \mathbb{R}^{m\times n}$ *and an integer* $1 \le k \le n$, $\mathbf{\Phi}$ *is said to satisfy the RIP of order k if there exists a constant* $\delta_k \in [0,1)$ *such that*

$$(1-\delta_k)\|\boldsymbol{x}\|_2^2 \le \|\mathbf{\Phi}\boldsymbol{x}\|_2^2 \le (1+\delta_k)\|\boldsymbol{x}\|_2^2 \tag{2.2}$$

holds for all k-sparse signals $\boldsymbol{x} \in \mathbb{R}^n$. *The smallest constant* δ_k *is called the restricted isometry constant (RIC) of order k for* $\mathbf{\Phi}$.

When k is not an integer, δ_k is defined as $\delta_{\lceil k\rceil}$ in [1], where $\lceil k\rceil$ denotes an integer satisfying $k \le \lceil k\rceil < k+1$.

The main result of [9] generalizes the recovery condition from [21] to the weighted ℓ_p-minimization (1.2) where the weight vector $\mathbf{w}$ is specified in (2.1).

Theorem 2.1 below states the main result of [9] which presents a sufficient condition for the exact recovery of sparse signal $\boldsymbol{x}$ from $\boldsymbol{y} = \mathbf{\Phi}\boldsymbol{x}$.

Theorem 2.1. *Let* $\boldsymbol{x}$ *be an arbitrary k-sparse vector in* $\mathbb{R}^n$ *with* $T = supp(\boldsymbol{x})$ *and* $\boldsymbol{y} = \mathbf{\Phi}\boldsymbol{x}$. *Let* $\widetilde{T} \subseteq [n]$ *be an arbitrary set and* $\rho \ge 0$ *and* $0 \le \alpha \le 1$ *with* $\alpha\rho \le 1$ *such that* $|\widetilde{T}| = \rho k$ *and* $|\widetilde{T} \cap T| = \alpha\rho k$. *Given the weight* $\omega \in [0, 1]$ *and* $0 < p \le 1$, *define some important parameters somehow depending on the weight* ω, *and the size and the overlap of the true signal support* T *and the prior support estimate* $\widetilde{T}$, *and* p *as follows*

- *The constant* ζ:

$$\zeta = \Big(\omega + (1-\omega)(1+\rho-2\alpha\rho)^{\frac{2-p}{2}}\Big)^{\frac{2}{2-p}}, \tag{2.3}$$

- *the constant* d:

$$d = \begin{cases} 1, & \omega = 1, \\ 1 + (\max\{0, 1-2\alpha\})\rho, & 0 \le \omega < 1, \end{cases} \tag{2.4}$$

- *the parameter* Θ *is defined by*

$$\Theta = \frac{\zeta}{t-d}, \tag{2.5}$$

- *for* $\Theta > 0$, *the quantity* $\delta(p,\Theta)$ *is defined by*

$$\delta(p,\Theta) = \begin{cases} \dfrac{1}{\sqrt{p^2+(2-p)^2\Theta}-(1-p)}, & \Theta \ge \Theta_0 = \dfrac{2+p}{2-p}, \\ \dfrac{z_0}{(2-p)\Theta - z_0}, & \Theta < \Theta_0, \end{cases} \tag{2.6}$$

where $z_0 \in ((1-p)\Theta, \min(1, \frac{2-p}{2}\Theta)$ *is the only positive solution of the equation*

$$\frac{p}{2}z^{\frac{2}{p}} + z - \frac{(2-p)\Theta}{2} = 0. \tag{2.7}$$

Moreover, for $\Theta = \frac{\zeta}{t-d} = 0$, *we define* $\delta(p,\Theta) = 1$.

If the measurement matrix $\mathbf{\Phi}$ *satisfies RIP with*

$$\delta_{tk} < \delta(p, \Theta) \tag{2.8}$$

for $d < t \leq 2d$*, then the weighted* ℓ_p*-minimization* (1.2) *with the weight vector* $\mathbf{w}$ *defined in* (2.1) *and* $0 < p \leq 1$ *recovers* $\boldsymbol{x}$ *exactly.*

3 Weighted ℓ_p-minimization with non-uniform weights

In this section, we present our main results for generalizing the weighted ℓ_p-minimization theory of [9], to allow for arbitrary weight assignments.

We consider the weighted ℓ_p-minimization with L distinct weights, where $1 \leq L \leq n$. Let $\widetilde{T}_j \subseteq [n]$ be arbitrary L disjoint sets and denote $\rho_j \geq 0$ and $0 \leq \alpha_j \leq 1$ such that $|\widetilde{T}_j| = \rho_j k$ and $|\widetilde{T}_j \cap T| = \alpha_j \rho_j k$, $j = 1, \cdots, L$, where $\rho_j \geq 0$ and $0 \leq \alpha_j \leq 1$ are called the relative size and accurary for each $j = 1, \cdots, L$. Define $\widetilde{T} = \cup_{j=1}^{L} \widetilde{T}_j$. The weight vector $\mathbf{w}$ in this general case is chosen in the following way

$$\mathrm{w}_i = \begin{cases} \omega_j, & i \in \widetilde{T}_j, \\ 1, & i \in \widetilde{T}^c, \end{cases} \tag{3.1}$$

for $i \in [n]$ and $\omega_j \in [0,1]$, $j = 1, \cdots, L$ are given weights.

We first provide a recovery guarantee for the weighted ℓ_p-minimization with L distinct weights in noiseless case.

Theorem 3.1. *For* $0 < p \leq 1$ *and* $\boldsymbol{y} = \mathbf{\Phi}\boldsymbol{x}$*, suppose that* $\boldsymbol{x}$ *be k-sparse with* $T = supp(\boldsymbol{x})$*. Let* $\widetilde{T}_i \subseteq [n]$ *be arbitrary L disjoint sets and* $\rho_i \geq 0$ *and* $0 \leq \alpha_i \leq 1$ *such that* $|\widetilde{T}_i| = \rho_i k$ *and* $|\widetilde{T}_i \cap T| = \alpha_i \rho_i k$*,* $i = 1, \cdots, L$*. Without loss of generality, assume that the weights in* (3.1) *are ordered so that* $0 \leq \omega_L \leq \cdots \leq \omega_1 \leq 1$*. Let*

$$\beta_i = \max\left\{ \sum_{j=i}^{L} \alpha_j \rho_j, \sum_{j=i}^{L} (1-\alpha_j)\rho_j \right\},$$

$$b_i = \begin{cases} 1, & i = 1, \\ sgn(\omega_{i-1} - \omega_i), & i = 2, \cdots, L, \end{cases}$$

and

$$d = \begin{cases} 1, & \omega_1 = \omega_2 = \cdots = \omega_L = 1, \\ \max\limits_{i \in \{1,2\cdots,L\}} \Big\{ b_i \Big(1 - \sum\limits_{j=i}^{L} \alpha_j \rho_j + \beta_i \Big) \Big\}, & 0 \le \prod\limits_{i=1}^{L} \omega_i < 1, \end{cases} \tag{3.2a}$$

$$\gamma_L = \omega_L + (1-\omega_1)\Big(1 + \sum_{i=1}^{L} \rho_i - 2\sum_{i=1}^{L} \alpha_i \rho_i\Big)^{\frac{2-p}{2}} + \sum_{i=2}^{L} (\omega_{i-1} - \omega_i)\Big(1 + \sum_{j=i}^{L} \rho_j - 2\sum_{j=i}^{L} \alpha_j \rho_j\Big)^{\frac{2-p}{2}}. \tag{3.2b}$$

If the measurement matrix $\mathbf{\Phi}$ *satisfies RIP and*

$$\delta_{tk} < \delta(t,\, p, \Theta), \tag{3.3}$$

where $d < t \le 2d$, *and for*

$$\Theta = \frac{\gamma_L^{2/(2-p)}}{t-d} > 0, \tag{3.4}$$

$\delta(t, p, \Theta)$ *is defined by*

$$\delta(t,p,\Theta) = \begin{cases} \dfrac{1}{\sqrt{p^2 + (2-p)^2\Theta} - (1-p)}, & \Theta \ge \Theta_0 = \dfrac{2+p}{2-p}, \\ \dfrac{z_0}{(2-p)\Theta - z_0}, & \Theta < \Theta_0, \end{cases} \tag{3.5}$$

where $z_0 \in \big((1-p)\Theta, \min(1, \frac{2-p}{2}\Theta)\big)$ *is the only positive solution of the equation*

$$\frac{p}{2} z^{\frac{2}{p}} + z - \frac{2-p}{2}\Theta = 0, \tag{3.6}$$

and

$$\delta(t,p,\Theta) = 1 \quad \text{if } \Theta = \frac{\gamma_L^{2/(2-p)}}{t-d} = 0,$$

then the weighted ℓ_p*-minimization* (1.2) *recovers* $\boldsymbol{x}$ *exactly.*

As $p=1$, Theorem 3.1 presents a sufficient condition of the weighted ℓ_1-minimization (1.3) for the exact recovery of $\boldsymbol{x}$, which improves the theory of [17]. See the following Corollary 3.1.

Corollary 3.1. *If* $p=1$ *and* $\mathbf{\Phi}$ *satisfies RIP with*

$$\delta_{tk} < \frac{1}{\sqrt{1+\Theta}}, \tag{3.7}$$

where $d < t \leq 2d$ *and*

$$\begin{aligned}\Theta =&(t-d)^{-1}\Bigg(\omega_L + (1-\omega_1)\sqrt{1+\sum_{i=1}^{L}\rho_i - 2\sum_{i=1}^{L}\alpha_i\rho_i}\\&+\sum_{i=2}^{L}(\omega_{i-1}-\omega_i)\sqrt{1+\sum_{j=i}^{L}\rho_j - 2\sum_{j=i}^{L}\alpha_j\rho_j}\Bigg)^2,\end{aligned}$$

then the weighted ℓ_1*-minimization* (1.3) *exactly recover* $\boldsymbol{x}$*.*

Remark 3.1. Note that the sufficient condition (3.7) is identical to the condition (3.1) in [8], since

$$\delta_{tk} < \frac{1}{\sqrt{1+\Theta}} = \sqrt{\frac{t-d}{t-d+\gamma_L^2}},$$

where the equality is from $\Theta = \frac{\gamma_L^2}{t-d}$ and

$$\begin{aligned}\gamma_L =&\omega_L + (1-\omega_1)\sqrt{1+\sum_{i=1}^{L}\rho_i - 2\sum_{i=1}^{L}\alpha_i\rho_i}\\&+\sum_{i=2}^{L}(\omega_{i-1}-\omega_i)\sqrt{1+\sum_{j=i}^{L}\rho_j - 2\sum_{j=i}^{L}\alpha_j\rho_j}.\end{aligned}\tag{3.8}$$

In noisy case, we have the following theorem.

Theorem 3.2. *For* $0 < p \leq 1$ *and* $\boldsymbol{y} = \boldsymbol{\Phi}\boldsymbol{x} + \boldsymbol{e}$*, suppose that* $\hat{\boldsymbol{x}}$ *is a minimizer of the weighted* ℓ_p*-minimization* (1.2) *with* $\|\boldsymbol{e}\|_2 \leq \varepsilon$*. If* $\boldsymbol{\Phi}$ *satisfies RIP with*

$$\delta_{tk} < \delta(t, p, \Theta) \tag{3.9}$$

for some $d < t \leq 2d$*, where* $\delta(t, p, \Theta)$ *is defined in* (3.5) *for* $\Theta > 0$*. Then*

$$\begin{aligned}&\|\boldsymbol{x}-\hat{\boldsymbol{x}}\|_2\\ \leq&\sqrt{2}\cdot\left[\frac{4(2-p)\eta(1-\eta)\sqrt{1+\delta_{tk}}+2\eta\sqrt{2(2-p)(1-p)(2-p-\eta)(\delta(t,p,\Theta)-\delta_{tk})}}{(2-p)(2-p-\eta)(\delta(t,p,\Theta)-\delta_{tk})}\right]\varepsilon,\end{aligned}$$

where

$$\eta = \begin{cases}\dfrac{2-p}{\sqrt{p^2+(2-p)^2\Theta}+p}, & \Theta \geq \Theta_0 = \dfrac{2+p}{2-p},\\ \dfrac{z_0}{\Theta}, & \Theta < \Theta_0,\end{cases}\tag{3.10}$$

and γ_L*,* z_0 *are defined as in Theorem* 3.1*.*

4 Proofs of the main results

4.1 Sparse representation and technical lemmas

The original work in [2] triggers an RIP analysis for signal recovery via l_1 minimization. The RIP analysis in [1] and [22] attains the summit for sparse signal recovery via l_1 minimization. The results in [1] and [22] depend on a key tool established in [20] and [1] independently, which represents points in a polytope

$$V = \{v \in \mathbb{R}^n,\ \|v\|_1 \le k\alpha,\ \|v\|_\infty \le \alpha \ \text{ for some } \alpha > 0\}$$

by convex combinations of $k-$sparse vectors. Zhang and Li [21] developed the tool, which extends the sparse representation of a polytope in [1] and [20] adapted to l_p, $(0 < p \le 1)$ case.

Lemma 4.1 ([21, Lemma 2.2]). *For $\boldsymbol{x} \in \mathbb{R}^n$ which satisfies $|\mathrm{supp}(\boldsymbol{x})| = K$, $\|\boldsymbol{x}\|_p^p \le L\rho^p$ and $\|\boldsymbol{x}\|_\infty \le \rho$ with $L \le K$ being a positive integer, ρ being a positive constant and $0 < p \le 1$, then $\boldsymbol{x}$ can be represented as the convex combination of L-sparse vectors, i.e.,*

$$\boldsymbol{x} = \sum_i \lambda_i \boldsymbol{u}_i,$$

where $\lambda_i > 0$, $\sum_i \lambda_i = 1$ and $\|\boldsymbol{u}_i\|_0 \le L$. Furthermore,

$$\sum_i \lambda_i \|\boldsymbol{u}_i\|_2^2 \le \min\Big\{\frac{n}{L}\|\boldsymbol{x}\|_2^2, \rho^p \|\boldsymbol{x}\|_{2-p}^{2-p}\Big\}. \tag{4.1}$$

For the weighted ℓ_p-minimization (1.2) with L distinct weights, the cone constraint inequality can be stated as follows.

Lemma 4.2. *If $\|\hat{\boldsymbol{x}}\|_{p,\mathbf{w}}^p \le \|\boldsymbol{x}\|_{p,\mathbf{w}}^p$ and $\boldsymbol{h} = \hat{\boldsymbol{x}} - \boldsymbol{x}$, then for any index set $\Gamma \subseteq [n]$,*

$$\begin{aligned}\|\boldsymbol{h}_{\Gamma^c}\|_p^p \le& \omega_L \|\boldsymbol{h}_\Gamma\|_p^p + (1-\omega_1)\|\boldsymbol{h}_{(\Gamma\cup\bigcup_{i=1}^L \widetilde{T}_i)\setminus(\bigcup_{i=1}^L \widetilde{T}_i\cap\Gamma)}\|_p^p \\ &+ \sum_{j=2}^L (\omega_{j-1}-\omega_j)\|\boldsymbol{h}_{(\Gamma\cup\bigcup_{i=j}^L \widetilde{T}_i)\setminus(\bigcup_{i=j}^L \widetilde{T}_i\cap\Gamma)}\|_p^p \\ &+ 2\Big(\omega\|\boldsymbol{x}_{\Gamma^c}\|_p^p + (1-\omega)\|\boldsymbol{x}_{\widetilde{T}^c\cap\Gamma^c}\|_p^p - \sum_{i=1}^L(\omega-\omega_i)\|\boldsymbol{x}_{\widetilde{T}_i\cap\Gamma^c}\|_p^p\Big),\end{aligned} \tag{4.2}$$

where

$$\widetilde{T} = \cup_{i=1}^L \widetilde{T}_i \quad \textit{and} \quad \omega = \sum_{i=1}^L \omega_i.$$

Proof. By $\hat{\boldsymbol{x}} = \boldsymbol{x} + \boldsymbol{h}$ and the choice of the weights in (3.1),

$$\|\hat{\boldsymbol{x}}\|_{p,\mathbf{w}}^p = \|\boldsymbol{x}+\boldsymbol{h}\|_{p,\mathbf{w}}^p \le \|\boldsymbol{x}\|_{p,\mathbf{w}}^p$$

implies

$$\sum_{i=1}^{L}\omega_i\|\boldsymbol{x}_{\widetilde{T}_i}+\boldsymbol{h}_{\widetilde{T}_i}\|_p^p+\|\boldsymbol{x}_{\widetilde{T}^c}+\boldsymbol{h}_{\widetilde{T}^c}\|_p^p\le\sum_{i=1}^{L}\omega_i\|\boldsymbol{x}_{\widetilde{T}_i}\|_p^p+\|\boldsymbol{x}_{\widetilde{T}^c}\|_p^p.$$

Furthermore, we have

$$\begin{aligned}&\sum_{i=1}^{L}(\omega_i\|\boldsymbol{x}_{\widetilde{T}_i\cap\Gamma}+\boldsymbol{h}_{\widetilde{T}_i\cap\Gamma}\|_p^p+\omega_i\|\boldsymbol{x}_{\widetilde{T}_i\cap\Gamma^c}+\boldsymbol{h}_{\widetilde{T}_i\cap\Gamma^c}\|_p^p)\\&\quad+\|\boldsymbol{x}_{\widetilde{T}^c\cap\Gamma}+\boldsymbol{h}_{\widetilde{T}^c\cap\Gamma}\|_p^p+\|\boldsymbol{x}_{\widetilde{T}^c\cap\Gamma^c}+\boldsymbol{h}_{\widetilde{T}^c\cap\Gamma^c}\|_p^p\\&\le\sum_{i=1}^{L}(\omega_i\|\boldsymbol{x}_{\widetilde{T}_i\cap\Gamma}\|_p^p+\omega_i\|\boldsymbol{x}_{\widetilde{T}_i\cap\Gamma^c}\|_p^p)+\|\boldsymbol{x}_{\widetilde{T}^c\cap\Gamma}\|_p^p+\|\boldsymbol{x}_{\widetilde{T}^c\cap\Gamma^c}\|_p^p.\end{aligned}$$

Next, we use the reverse triangle inequality to get

$$\begin{aligned}&\sum_{i=1}^{L}\omega_i\|\boldsymbol{h}_{\widetilde{T}_i\cap\Gamma^c}\|_p^p+\|\boldsymbol{h}_{\widetilde{T}^c\cap\Gamma^c}\|_p^p\\&\le\sum_{i=1}^{L}\omega_i\|\boldsymbol{h}_{\widetilde{T}_i\cap\Gamma}\|_p^p+\|\boldsymbol{h}_{\widetilde{T}^c\cap\Gamma}\|_p^p+2\Big(\sum_{i=1}^{L}\omega_i\|\boldsymbol{x}_{\widetilde{T}_i\cap\Gamma^c}\|_p^p+\|\boldsymbol{x}_{\widetilde{T}^c\cap\Gamma^c}\|_p^p\Big).\end{aligned}\tag{4.3}$$

Now, we can write

$$\|\boldsymbol{h}_{\Gamma^c}\|_p^p=\sum_{i=1}^{L}\|\boldsymbol{h}_{\widetilde{T}_i\cap\Gamma^c}\|_p^p+\|\boldsymbol{h}_{\widetilde{T}^c\cap\Gamma^c}\|_p^p.$$

Let us add and subtract $\omega_i\|\boldsymbol{h}_{\widetilde{T}_j\cap\Gamma^c}\|_p^p$ for all pairs of i and j such that $i,j=1,\cdots,L$ and $i\neq j$, and $\omega_i\|\boldsymbol{h}_{\widetilde{T}^c\cap\Gamma^c}\|_p^p$ for $i=1,\cdots,L$ to the left side of (4.3). Then the left side of (4.3) becomes

$$\begin{aligned}&\sum_{i=1}^{L}\omega_i\|\boldsymbol{h}_{\widetilde{T}_i\cap\Gamma^c}\|_p^p+\|\boldsymbol{h}_{\widetilde{T}^c\cap\Gamma^c}\|_p^p+\sum_{i,j,i\neq j}\omega_i\|\boldsymbol{h}_{\widetilde{T}_j\cap\Gamma^c}\|_p^p-\sum_{i\neq j}\omega_i\|\boldsymbol{h}_{\widetilde{T}_j\cap\Gamma^c}\|_p^p\\&\quad+\sum_{i=1}^{L}\omega_i\|\boldsymbol{h}_{\widetilde{T}^c\cap\Gamma^c}\|_p^p-\sum_{i=1}^{L}\omega_i\|\boldsymbol{h}_{\widetilde{T}^c\cap\Gamma^c}\|_p^p\\&=\sum_{i=1}^{L}\omega_i\Big(\|\boldsymbol{h}_{\widetilde{T}_i\cap\Gamma^c}\|_p^p+\sum_{j\neq i}\|\boldsymbol{h}_{\widetilde{T}_j\cap\Gamma^c}\|_p^p\Big)-\sum_{i\neq j}\omega_i\|h_{\widetilde{T}_j\cap\Gamma^c}\|_p^p+(1-\omega)\|\boldsymbol{h}_{\widetilde{T}^c\cap\Gamma^c}\|_p^p+\sum_{i=1}^{L}\omega_i\|\boldsymbol{h}_{\widetilde{T}^c\cap\Gamma^c}\|_p^p\\&=\omega\|\boldsymbol{h}_{\Gamma^c}\|_p^p+(1-\omega)\|\boldsymbol{h}_{\widetilde{T}^c\cap\Gamma^c}\|_p^p-\sum_{j=1}^{L}\Big(\sum_{i\neq j}\omega_i\Big)\|\boldsymbol{h}_{\widetilde{T}_j\cap\Gamma^c}\|_p^p\\&=\omega\|\boldsymbol{h}_{\Gamma^c}\|_p^p+(1-\omega)\|\boldsymbol{h}_{\widetilde{T}^c\cap\Gamma^c}\|_p^p-\sum_{j=1}^{L}(\omega-\omega_j)\|\boldsymbol{h}_{\widetilde{T}_j\cap\Gamma^c}\|_p^p.\end{aligned}$$

Similarly, we can write

$$\|\boldsymbol{h}_{\Gamma}\|_p^p=\sum_{i=1}^{L}\|\boldsymbol{h}_{\widetilde{T}_i\cap\Gamma}\|_p^p+\|\boldsymbol{h}_{\widetilde{T}^c\cap\Gamma}\|_p^p.$$

Let us add and subtract $\omega_i\|\boldsymbol{h}_{\widetilde{T}_j\cap\Gamma}\|_p^p$ for all pairs of i and j such that $i,j=1,\cdots,L$ and $i\neq j$, and $\omega_i\|\boldsymbol{h}_{\widetilde{T}^c\cap\Gamma}\|_p^p$ for $i=1,\cdots,L$ to the right side of (4.3), as well as $\omega_i\|\boldsymbol{x}_{\widetilde{T}_j\cap\Gamma^c}\|_p^p$ for $i=1,\cdots,L$ and $i\neq j$, and $\omega_i\|\boldsymbol{x}_{\widetilde{T}^c\cap\Gamma^c}\|_p^p$ for $i=1,\cdots,L$. Then the right side of (4.3) becomes

$$\begin{aligned}&\omega\|\boldsymbol{h}_{\Gamma}\|_p^p+(1-\omega)\|\boldsymbol{h}_{\widetilde{T}^c\cap\Gamma}\|_p^p-\sum_{i=1}^{L}(\omega-\omega_i)\|\boldsymbol{h}_{\widetilde{T}_i\cap\Gamma}\|_p^p\\&\quad+2\Big(\omega\|\boldsymbol{x}_{\Gamma^c}\|_p^p+(1-\omega)\|\boldsymbol{x}_{\widetilde{T}^c\cap\Gamma^c}\|_p^p-\sum_{i=1}^{L}(\omega-\omega_i)\|\boldsymbol{x}_{\widetilde{T}_i\cap\Gamma^c}\|_p^p\Big).\end{aligned}$$

Let

$$D=\omega\|\boldsymbol{x}_{\Gamma^c}\|_p^p+(1-\omega)\|\boldsymbol{x}_{\widetilde{T}^c\cap\Gamma^c}\|_p^p-\sum_{i=1}^{L}(\omega-\omega_i)\|\boldsymbol{x}_{\widetilde{T}_i\cap\Gamma^c}\|_p^p.$$

Putting these together, we have

$$\begin{aligned}&\omega\|\boldsymbol{h}_{\Gamma^c}\|_p^p+(1-\omega)\|\boldsymbol{h}_{\widetilde{T}^c\cap\Gamma^c}\|_p^p-\sum_{i=1}^{L}(\omega-\omega_i)\|\boldsymbol{h}_{\widetilde{T}_i\cap\Gamma^c}\|_p^p\\\le&\omega\|\boldsymbol{h}_{\Gamma}\|_p^p+(1-\omega)\|\boldsymbol{h}_{\widetilde{T}^c\cap\Gamma}\|_p^p-\sum_{i=1}^{L}(\omega-\omega_i)\|\boldsymbol{h}_{\widetilde{T}_i\cap\Gamma}\|_p^p+2D.\end{aligned}\tag{4.4}$$

But, we can also write $\|\boldsymbol{h}_{\Gamma^c}\|_p^p$ as

$$\|\boldsymbol{h}_{\Gamma^c}\|_p^p=\omega\|\boldsymbol{h}_{\Gamma^c}\|_p^p+\sum_{i=1}^{L}(1-\omega)\|\boldsymbol{h}_{\widetilde{T}_i\cap\Gamma^c}\|_p^p+(1-\omega)\|\boldsymbol{h}_{\widetilde{T}^c\cap\Gamma^c}\|_p^p.$$

Solving for $\omega\|\boldsymbol{h}_{\Gamma^c}\|_p^p$ and substituting into (4.4) gives

$$\begin{aligned}&\|\boldsymbol{h}_{\Gamma^c}\|_p^p-\sum_{i=1}^{L}(1-\omega)\|\boldsymbol{h}_{\widetilde{T}_i\cap\Gamma^c}\|_p^p-(1-\omega)\|\boldsymbol{h}_{\widetilde{T}^c\cap\Gamma^c}\|_p^p\\&\quad+(1-\omega)\|\boldsymbol{h}_{\widetilde{T}^c\cap\Gamma^c}\|_p^p-\sum_{i=1}^{L}(\omega-\omega_i)\|\boldsymbol{h}_{\widetilde{T}_i\cap\Gamma^c}\|_p^p\\\le&\omega\|\boldsymbol{h}_{\Gamma}\|_p^p+(1-\omega)\|\boldsymbol{h}_{\widetilde{T}^c\cap\Gamma}\|_p^p-\sum_{i=1}^{L}(\omega-\omega_i)\|\boldsymbol{h}_{\widetilde{T}_i\cap\Gamma}\|_p^p+2D.\end{aligned}$$

Simplifying, we get

$$
\begin{aligned}
\|h_{\Gamma^c}\|_p^p \leq& \sum_{i=1}^{L}(1-\omega)\|h_{\widetilde{T}_i\cap\Gamma^c}\|_p^p + \sum_{i=1}^{L}(\omega-\omega_i)\|h_{\widetilde{T}_i\cap\Gamma^c}\|_p^p + \omega\|h_\Gamma\|_p^p \\
&+ (1-\omega)\|h_{\widetilde{T}^c\cap\Gamma}\|_p^p - \sum_{i=1}^{L}(\omega-\omega_i)\|h_{\widetilde{T}_i\cap\Gamma}\|_p^p + 2D \\
=& \sum_{i=1}^{L}(1-\omega_i)\|h_{\widetilde{T}_i\cap\Gamma^c}\|_p^p + \omega\|h_\Gamma\|_p^p + \|h_{\widetilde{T}^c\cap\Gamma}\|_p^p \\
&- \sum_{i=1}^{L}\omega_i\Big(\|h_{\widetilde{T}^c\cap\Gamma}\|_p^p + \sum_{j=1,j\neq i}^{L}\|h_{\widetilde{T}_j\cap\Gamma}\|_p^p\Big) + 2D \\
=& \sum_{i=1}^{L}(1-\omega_i)\|h_{\widetilde{T}_i\cap\Gamma^c}\|_p^p + \omega\|h_\Gamma\|_p^p + \|h_{\widetilde{T}^c\cap\Gamma}\|_p^p - \sum_{i=1}^{L}\omega_i\|h_{\widetilde{T}_i^c\cap\Gamma}\|_p^p \\
&+ \sum_{i=1}^{L}\|h_{\widetilde{T}_i^c\cap\Gamma}\|_p^p - \sum_{i=1}^{L}\|h_{\widetilde{T}_i^c\cap\Gamma}\|_p^p + 2D \qquad (4.5) \\
=&\omega\|h_\Gamma\|_p^p + \|h_{\widetilde{T}^c\cap\Gamma}\|_p^p - \sum_{i=1}^{L}\|h_{\widetilde{T}_i^c\cap\Gamma}\|_p^p + \sum_{i=1}^{L}(1-\omega_i)\Big(\|h_{\widetilde{T}_i\cap\Gamma^c}\|_p^p + \|h_{\widetilde{T}_i^c\cap\Gamma}\|_p^p\Big) + 2D \\
=&(\omega-(L-1))\|h_\Gamma\|_p^p + \sum_{i=1}^{L}(1-\omega_i)\Big(\|h_{\widetilde{T}_i\cap\Gamma^c}\|_p^p + \|h_{\widetilde{T}_i\cap\Gamma}\|_p^p\Big) + 2D, \qquad (4.6)
\end{aligned}
$$

where in (4.5) we have added zero and observed that

$$\|h_{\widetilde{T}^c\cap\Gamma}\|_p^p + \sum_{j=1,j\neq i}^{L}\|h_{\widetilde{T}_j\cap\Gamma}\|_p^p = \|h_{\widetilde{T}_i^c\cap\Gamma}\|_p^p$$

and in (4.6), we have observed that

$$\sum_{i=1}^{L}\|h_{\widetilde{T}_i^c\cap\Gamma}\|_p^p = (L-1)\|h_\Gamma\|_p^p + \|h_{\widetilde{T}^c\cap\Gamma}\|_p^p.$$

Then assuming, without loss of generality, $\omega_1 \geq \omega_2 \geq \cdots \geq \omega_L$, and writing $1-\omega_i = 1-\omega_1+\omega_1-\omega_i$ for $i>1$, we have

$$
\begin{aligned}
\|h_{\Gamma^c}\|_p^p \leq&(\omega-(L-1))\|h_\Gamma\|_p^p + (1-\omega_1)\sum_{i=1}^{L}\Big(\|h_{\widetilde{T}_i^c\cap\Gamma}\|_p^p + \|h_{\widetilde{T}_i\cap\Gamma^c}\|_p^p\Big) \\
&+ \sum_{i=2}^{L}(\omega_1-\omega_i)\Big(\|h_{\widetilde{T}_i^c\cap\Gamma}\|_p^p + \|h_{\widetilde{T}_i\cap\Gamma^c}\|_p^p\Big) + 2D. \qquad (4.7)
\end{aligned}
$$

Next, write $\omega_1-\omega_i=\omega_1-\omega_2+\omega_2-\omega_i$ for $i>2$. Then we have

$$\begin{aligned}\|\boldsymbol{h}_{\Gamma^c}\|_p^p \leq&(\omega-(L-1))\|\boldsymbol{h}_\Gamma\|_p^p+(1-\omega_1)\sum_{i=1}^{L}\left(\|\boldsymbol{h}_{\widetilde{T}_i^c\cap\Gamma}\|_p^p+\|\boldsymbol{h}_{\widetilde{T}_i\cap\Gamma^c}\|_p^p\right)+(\omega_1-\omega_2)\\&\times\sum_{i=2}^{L}\left(\|\boldsymbol{h}_{\widetilde{T}_i^c\cap\Gamma}\|_p^p+\|\boldsymbol{h}_{\widetilde{T}_i\cap\Gamma^c}\|_p^p\right)+\sum_{i=3}^{L}(\omega_2-\omega_i)\left(\|\boldsymbol{h}_{\widetilde{T}_i^c\cap\Gamma}\|_p^p+\|\boldsymbol{h}_{\widetilde{T}_i\cap\Gamma^c}\|_p^p\right)\\&+2D. \qquad (4.8)\end{aligned}$$

Continuing in this way gives us

$$\begin{aligned}\|\boldsymbol{h}_{\Gamma^c}\|_p^p \leq&(\omega-(L-1))\|\boldsymbol{h}_\Gamma\|_p^p+(1-\omega_1)\sum_{i=1}^{L}\left(\|\boldsymbol{h}_{\widetilde{T}_i^c\cap\Gamma}\|_p^p+\|\boldsymbol{h}_{\widetilde{T}_i\cap\Gamma^c}\|_p^p\right)\\&+\sum_{j=2}^{L}(\omega_{j-1}-\omega_j)\sum_{i=j}^{L}\left(\|\boldsymbol{h}_{\widetilde{T}_i^c\cap\Gamma}\|_p^p+\|\boldsymbol{h}_{\widetilde{T}_i\cap\Gamma^c}\|_p^p\right)+2D. \qquad (4.9)\end{aligned}$$

Noting

$$\begin{aligned}&\|\boldsymbol{h}_{\widetilde{T}_i^c\cap\Gamma}\|_p^p=\sum_{j=1,j\neq i}^{L}\|\boldsymbol{h}_{\widetilde{T}_j\cap\Gamma}\|_p^p+\|\boldsymbol{h}_{\Gamma\cap\bigcap_{j=1}^L\widetilde{T}_j^c}\|_p^p,\\&\|\boldsymbol{h}_\Gamma\|_p^p=\sum_{i=1}^{L}\|\boldsymbol{h}_{\widetilde{T}_i\cap\Gamma}\|_p^p+\|\boldsymbol{h}_{\Gamma\cap\bigcap_{j=1}^L\widetilde{T}_j^c}\|_p^p,\\&\sum_{i=j}^{L}\|\boldsymbol{h}_{\widetilde{T}_i\cap\Gamma^c}\|_p^p+\|\boldsymbol{h}_{\Gamma\cap\bigcap_{i=j}^L\widetilde{T}_i^c}\|_p^p=\|\boldsymbol{h}_{\Gamma\cup\bigcup_{i=j}^L\widetilde{T}_i\setminus\bigcup_{i=j}^L(\widetilde{T}_i\cap\Gamma)}\|_p^p,\end{aligned}$$

for any $j=1,2,\cdots,L$, the above inequality can also be expressed as

$$\begin{aligned}\|h_{\Gamma^c}\|_p^p \leq&(\omega-(L-1))\|\boldsymbol{h}_\Gamma\|_p^p+(1-\omega_1)\left((L-1)\|\boldsymbol{h}_\Gamma\|_p^p+\|\boldsymbol{h}_{\Gamma\cup\bigcup_{i=1}^L\widetilde{T}_i\setminus\bigcup_{i=1}^L(\widetilde{T}_i\cap\Gamma)}\|_p^p\right)\\&+\sum_{j=2}^{L}(\omega_{j-1}-\omega_j)\left((L-j)\|\boldsymbol{h}_\Gamma\|_p^p+\|\boldsymbol{h}_{\Gamma\cup\bigcup_{i=j}^L\widetilde{T}_i\setminus\bigcup_{i=j}^L(\widetilde{T}_i\cap\Gamma)}\|_p^p\right)+2D. \qquad (4.10)\end{aligned}$$

Combining the coefficients of $\|\boldsymbol{h}_\Gamma\|_p^p$, we have

$$\begin{aligned}&\sum_{i=1}^{L}\omega_i-(L-1)+(1-\omega_1)(L-1)+\sum_{j=2}^{L}(\omega_{j-1}-\omega_j)(L-j)\\=&\sum_{i=1}^{L}\omega_i-(L-1)\omega_1+(L-2)\omega_1+\sum_{j=2}^{L-1}(L-(j+1))\omega_j-\sum_{j=2}^{L-1}(L-j)\omega_j\\=&\sum_{i=2}^{L}\omega_i-\sum_{j=2}^{L-1}\omega_j=\omega_L.\end{aligned}$$

Finally, we obtain that

$$\begin{aligned}\|\boldsymbol{h}_{\Gamma^c}\|_p^p \leq & \omega_L \|\boldsymbol{h}_\Gamma\|_p^p + (1-\omega_1)\|\boldsymbol{h}_{\Gamma\cup\bigcup_{i=1}^L \widetilde{T}_i \setminus \bigcup_{i=1}^L (\widetilde{T}_i\cap\Gamma)}\|_p^p \\ & + \sum_{j=2}^{L}(\omega_{j-1}-\omega_j)\|\boldsymbol{h}_{\Gamma\cup\bigcup_{i=j}^L \widetilde{T}_i \setminus \bigcup_{i=j}^L (\widetilde{T}_i\cap\Gamma)}\|_p^p + 2D.\end{aligned}$$

Thus, we complete the proof. □

The following two technical lemmas will be used to simplify the proof of our main results.

Lemma 4.3 ([9, Lemma V.1]). *Let p and q be two positive numbers. Then*

(a) $\|\boldsymbol{x}\|_p \leq \|\boldsymbol{x}\|_2 |\mathrm{supp}(\boldsymbol{x})|^{\frac{2-p}{2p}}$, *if* $0<p<2$,

(b) $\|\boldsymbol{x}\|_p^p \leq (\|\boldsymbol{x}\|_2^2)^{\frac{1}{q}} (\|\boldsymbol{x}\|_{p_1}^{p_1})^{1-\frac{1}{q}}$, *if* $pq>2$ *and* $q>1$, *where* $p_1=(p-\frac{2}{q})(\frac{q}{q-1})$.

Lemma 4.4 ([9, Lemma V.2]). *For $0<p\leq 1$ and $\Lambda>0$, the function*

$$g(z)=\frac{p}{2}z^{\frac{2}{p}}+z-\frac{2-p}{2}\Lambda$$

is monotone increasing in $(0,\infty)$. In addition, the following statements hold:

(I) If $0<\Lambda\leq\frac{2}{2-p}$, there exists a unique point $z_0\in((1-p)\Lambda,(1-\frac{p}{2})\Lambda)\subseteq(0,1)$ such that $g(z_0)=0$.

(II) If $\frac{2}{2-p}<\Lambda<\frac{2+p}{2-p}$, there exists a unique point $z_0\in((1-p)\Lambda,1)\subseteq(0,1)$ such that $g(z_0)=0$.

(III) If $\Lambda\geq\frac{2+p}{2-p}$, there does not exist a point $z_0\in(0,\,1)$ such that $g(z_0)=0$.

4.2 Proof of Theorem 3.1

Proof. We assume that tk is an integer. When tk is not an integer, it can be treated as in [1] and [9]. Let $\boldsymbol{h}=\hat{\boldsymbol{x}}-\boldsymbol{x}$, where $\hat{\boldsymbol{x}}$ is a minimizer of the weighted ℓ_p-minimization problem (1.2) with $\epsilon=0$. Then

$$\boldsymbol{\Phi h}=\boldsymbol{0}. \tag{4.11}$$

We prove $\boldsymbol{h}=\boldsymbol{0}$ to show that $\boldsymbol{x}$ could be recovered exactly via the weighted ℓ_p-minimization (1.2).

On the contrary, we suppose here that $\boldsymbol{h}\neq\boldsymbol{0}$, then $\boldsymbol{h}_{\max(dk)}\neq\boldsymbol{0}$, where $\boldsymbol{h}_{\max(dk)}$ is the best dk-term approximation of $\boldsymbol{h}$ and we define

$$\boldsymbol{h}_{-\max(dk)}=\boldsymbol{h}-\boldsymbol{h}_{\max(dk)}.$$

Since T is the support set of the k-sparse vector $\boldsymbol{x}$, we know that $|T| \leq k$. Recall the definition of d in (3.2a),

$$d = \begin{cases} 1, & \omega_1 = \cdots = \omega_L = 1, \\ \max\limits_{i \in \{1,2\cdots,L\}} \Big\{ b_i \Big(1 - \sum\limits_{j=i}^{L} \alpha_j \rho_j + \beta_i \Big) \Big\}, & 0 \leq \prod\limits_{i=1}^{L} \omega_i < 1, \end{cases} \tag{4.12}$$

where

$$\beta_i = \max \Big\{ \sum_{j=i}^{L} \alpha_j \rho_j, \sum_{j=i}^{L} (1-\alpha_j) \rho_j \Big\},$$
$$b_i = \begin{cases} 1, & i = 1, \\ sgn(\omega_{i-1} - \omega_i), & i = 2, \cdots, L. \end{cases}$$

It is clear that $d \geq 1$ and dk is an integer. Thus,

$$\begin{aligned} & \|\boldsymbol{h}_{-\max(dk)}\|_p^p \leq \|\boldsymbol{h}_{T^c}\|_p^p \\ \leq & \omega_L \|\boldsymbol{h}_T\|_p^p + (1-\omega_1) \|\boldsymbol{h}_{T \cup \bigcup_{i=1}^{L} \widetilde{T}_i \setminus \bigcup_{i=1}^{L} (\widetilde{T}_i \cap T)}\|_p^p \\ & \quad + \sum_{j=2}^{L} (\omega_{j-1} - \omega_j) \|\boldsymbol{h}_{T \cup \bigcup_{i=j}^{L} \widetilde{T}_i \setminus \bigcup_{i=j}^{L} (\widetilde{T}_i \cap T)}\|_p^p \qquad (4.13) \\ \leq & \begin{cases} \|\boldsymbol{h}_T\|_p^p, & \omega_1 = \cdots = \omega_L = 1, \\ \omega_L \|\boldsymbol{h}_T\|_p^p + (1-\omega_L) \|\boldsymbol{h}_{\max(dk)}\|_p^p, & 0 \leq \prod\limits_{i=1}^{L} \omega_i < 1, \end{cases} \qquad (4.14) \end{aligned}$$

where the first inequality is from $d \geq 1$ and $|T| \leq k$, the second inequality follows from Lemma 4.2 with $\Gamma = T$ and the last inequality is due to

$$\Big| \Big(T \cup \bigcup_{j=i}^{L} \widetilde{T}_j \Big) \Big\backslash \bigcup_{j=i}^{L} \Big(T \cap \widetilde{T}_j \Big) \Big| \leq k + \sum_{j=i}^{L} \rho_j k - 2 \sum_{j=i}^{L} \alpha_j \rho_j k = k \Big(1 + \sum_{j=i}^{L} \rho_j - 2 \sum_{j=i}^{L} \alpha_j \rho_j \Big) \leq dk$$

with

$$\beta_i = \max \Big\{ \sum_{j=i}^{L} \alpha_j \rho_j, \sum_{j=i}^{L} (1-\alpha_j) \rho_j \Big\}.$$

Let

$$\nu = \Big(\frac{\omega_L \|\boldsymbol{h}_T\|_p^p + (1-\omega_1) \|\boldsymbol{h}_{T \cup \bigcup_{i=1}^{L} \widetilde{T}_i \setminus \bigcup_{i=1}^{L} (\widetilde{T}_i \cap T)}\|_p^p + \sum_{j=2}^{L} (\omega_{j-1} - \omega_j) \|\boldsymbol{h}_{T \cup \bigcup_{i=1}^{L} \widetilde{T}_i \setminus \bigcup_{i=1}^{L} (\widetilde{T}_i \cap \mathbb{T})}\|_p^p}{k(t-d)} \Big)^{\frac{1}{p}}. \tag{4.15}$$

Then $\nu \geq 0$. First, we suppose that $\nu = 0$, then we have $\|\boldsymbol{h}_{T^c}\|_p^p = 0$ by (4.13), which implies $\boldsymbol{h}$ is k-sparse. Since the sensing matrix $\boldsymbol{\Phi}$ satisfies the RIP of order tk with $t > d \geq 1$ and (4.11), we have $\boldsymbol{h} = \boldsymbol{0}$. Therefore, $\boldsymbol{x}$ is exactly recovered by (1.2) with $\epsilon = 0$.

For $\nu > 0$, we divide the vector $\boldsymbol{h}_{-\max(dk)}$ into two parts, i.e.,

$$\boldsymbol{h}_{-\max(dk)} = \boldsymbol{h}^{(1)} + \boldsymbol{h}^{(2)}, \tag{4.16}$$

where

$$\boldsymbol{h}^{(1)} = \boldsymbol{h}_{-\max(dk)} \cdot \chi_{\{i \mid |\boldsymbol{h}_{-\max(dk)}(i)| > \nu\}}, \tag{4.17a}$$

$$\boldsymbol{h}^{(2)} = \boldsymbol{h}_{-\max(dk)} \cdot \chi_{\{i \mid |\boldsymbol{h}_{-\max(dk)}(i)| \leq \nu\}}. \tag{4.17b}$$

Then

$$\|\boldsymbol{h}^{(1)}\|_p^p \leq \|\boldsymbol{h}_{-\max(dk)}\|_p^p \leq k(t-d)\nu^p$$

by (4.13) and (4.15). Denote $|\mathrm{supp}(\boldsymbol{h}^{(1)})| = \|\boldsymbol{h}^{(1)}\|_0 = m$. Since all non-zero entries of $\boldsymbol{h}^{(1)}$ have absolute value larger than ν, we have

$$(t-d)k\nu^p \geq \|\boldsymbol{h}_{-\max(dk)}\|_p^p \geq \|\boldsymbol{h}^{(1)}\|_p^p = \sum_{i \in \mathrm{supp}(\boldsymbol{h}^{(1)})} |\boldsymbol{h}^{(1)}(i)|^p \geq m\nu^p. \tag{4.18}$$

By (4.18) and $\nu \neq 0$, one has

$$|\mathrm{supp}(\boldsymbol{h}^{(1)})| = m \leq (t-d)k$$

and

$$|\mathrm{supp}(\boldsymbol{h}_{\max(dk)}) + \mathrm{supp}(\boldsymbol{h}^{(1)})| \leq dk + |\mathrm{supp}(\boldsymbol{h}^{(1)})| \leq dk + (t-d)k = tk. \tag{4.19}$$

Moreover,

$$\|\boldsymbol{h}^{(2)}\|_\infty \overset{(a)}{\leq} \nu, \quad \|\boldsymbol{h}^{(2)}\|_p^p \overset{(b)}{=} \|\boldsymbol{h}_{-\max(dk)}\|_p^p - \|\boldsymbol{h}^{(1)}\|_p^p \overset{(c)}{\leq} ((t-d)k - m)\nu^p, \tag{4.20}$$

where (a) is from (4.17b), (b) is due to (4.16) and (c) follows from (4.18). Applying Lemma 4.1 with $L = k(t-d) - m$ and $\rho = \nu$, we can express $\boldsymbol{h}^{(2)}$ as a convex combination of $(k(t-d)-m)$-sparse vectors, i.e., $\boldsymbol{h}^{(2)} = \sum_i \lambda_i \boldsymbol{u_i}$, where $\lambda_i > 0$, $\sum_i \lambda_i = 1$, $\boldsymbol{u_i}$ is $(k(t-d)-m)$-sparse and $\mathrm{supp}(\boldsymbol{u_i}) \subseteq \mathrm{supp}(\boldsymbol{h}^{(2)})$. By (4.16), we have

$$\langle \boldsymbol{h}_{\max(dk)} + \boldsymbol{h}^{(1)}, \boldsymbol{u_i} \rangle = 0. \tag{4.21}$$

Furthermore, by (4.1),

$$\begin{aligned}
\Sigma_i \lambda_i \|\boldsymbol{u_i}\|_2^2 &\leq \min\left\{\frac{n}{L}\|\boldsymbol{h}^{(2)}\|_2^2, \nu^p \|\boldsymbol{h}^{(2)}\|_{2-p}^{2-p}\right\} \leq \nu^p \|\boldsymbol{h}^{(2)}\|_{2-p}^{2-p} \\
&\leq \nu^p (\|\boldsymbol{h}^{(2)}\|_2^2)^{\frac{2-2p}{2-p}} (\|\boldsymbol{h}^{(2)}\|_p^p)^{\frac{p}{2-p}} \\
&\leq \nu^p (\|\boldsymbol{h}^{(2)}\|_2^2)^{\frac{2-2p}{2-p}} \Big(((t-d)k - m)\nu^p\Big)^{\frac{p}{2-p}} \\
&\leq (\|\boldsymbol{h}^{(2)}\|_2^2)^{\frac{2-2p}{2-p}} \Big(k(t-d)\nu^2\Big)^{\frac{p}{2-p}},
\end{aligned} \tag{4.22}$$

where the third inequality is from Lemma 4.3(b), and the fourth inequality follows from (4.20). By (4.15), we have

$$\begin{aligned}
&k(t-d)\nu^2\\
=&(k(t-d))^{1-\frac{2}{p}}\Big(\omega_L\|\boldsymbol{h}_{\mathbb{T}}\|_p^p+(1-\omega_1)\|\boldsymbol{h}_{T\cup\bigcup_{i=1}^L\widetilde{T}_i\setminus\bigcup_{i=1}^L(\widetilde{T}_i\cap T)}\|_p^p\\
&+\sum_{j=2}^L(\omega_{j-1}-\omega_j)\|\boldsymbol{h}_{T\cup\bigcup_{i=1}^L\widetilde{T}_i\setminus\bigcup_{i=1}^L(\widetilde{T}_i\cap T)}\|_p^p\Big)^{\frac{2}{p}}\\
\leq&(k(t-d))^{1-\frac{2}{p}}\Big(\omega_L|T|^{\frac{2-p}{2}}\|\boldsymbol{h}_T\|_p^p\\
&+(1-\omega_1)|T\cup\bigcup_{i=1}^L\widetilde{T}_i\setminus\bigcup_{i=1}^L(\widetilde{T}_i\cap T)|^{\frac{2-p}{2}}\|\boldsymbol{h}_{\mathbb{T}}\|_p^p+(1-\omega_1)\|\boldsymbol{h}_{T\cup\bigcup_{i=1}^L\widetilde{T}_i\setminus\bigcup_{j=i}^L(\widetilde{T}_i\cap T)}\|_2^p\\
&+\sum_{i=2}^L(\omega_{i-1}-\omega_i)|\bigcup_{j=i}^L\widetilde{T}_i\setminus\bigcup_{j=i}^L(\widetilde{T}_j\cap T)|^{\frac{2-p}{2}}\|\boldsymbol{h}_T\|_p^p+(1-\omega_1)\|\boldsymbol{h}_{T\cup\bigcup_{j=i}^L\widetilde{T}_j\setminus\bigcup_{j=i}^L(\widetilde{T}_j\cap T)}\|_2^p)\Big)^{\frac{2}{p}}\\
\leq&(k(t-d))^{1-\frac{2}{p}}k^{\frac{2-p}{p}}\Big(\omega_L+(1-\omega_1)\Big(1+\sum_{j=1}^L\rho_j-2\sum_{j=1}^L\alpha_j\rho_j\Big)^{\frac{2-p}{2}}\\
&+\sum_{i=2}^L(\omega_{i-1}-\omega_i)\Big(1+\sum_{j=1}^L\rho_j-2\sum_{j=1}^L\alpha_j\rho_j\Big)^{\frac{2-p}{2}}\Big)^{\frac{2}{p}}\|\boldsymbol{h}_{\max(dk)}+\boldsymbol{h}^{(1)}\|_2^2\\
=&(t-d)^{1-\frac{2}{p}}\Big(\omega_L+(1-\omega_1)\Big(1+\sum_{j=1}^L\rho_j-2\sum_{j=1}^L\alpha_j\rho_j\Big)^{\frac{2-p}{2}}\\
&+\sum_{i=2}^L(\omega_{i-1}-\omega_i)\Big(1+\sum_{j=1}^L\rho_j-2\sum_{j=1}^L\alpha_j\rho_j\Big)^{\frac{2-p}{2}}\Big)^{\frac{2}{p}}\|\boldsymbol{h}_{\max(dk)}+\boldsymbol{h}^{(1)}\|_2^2, \qquad (4.23)
\end{aligned}$$

where the first inequality is due to $0<p\leq 1$ and Lemma 4.3(a) and the second inequality is from $|T|\leq k$ and

$$\begin{aligned}
&\Big|T\cup\bigcup_{j=i}^L\tilde{T}_j\Big\backslash\bigcup_{j=i}^L(T\cap\tilde{T}_j)\Big|\\
=&k+\sum_{j=i}^L\rho_jk-2\sum_{j=i}^L\alpha_j\rho_jk=k\Big(1+\sum_{j=i}^L\rho_j-2\sum_{j=i}^L\alpha_j\rho_j\Big)\leq dk.
\end{aligned}$$

Then, by (4.22) and (4.23),

$$\begin{aligned}
\sum_i\lambda_i\|\boldsymbol{u_i}\|_2^2\leq&(\|\boldsymbol{h}^{(2)}\|_2^2)^{\frac{2-2p}{2-p}}(t-d)^{-1}\Big(\omega_L+(1-\omega_1)\Big(1+\sum_{j=1}^L\rho_j-2\sum_{j=1}^L\alpha_j\rho_j\Big)^{\frac{2-p}{2}}\\
&+\sum_{i=2}^L(\omega_{i-1}-\omega_i)\Big(1+\sum_{j=1}^L\rho_j-2\sum_{j=1}^L\alpha_j\rho_j\Big)^{\frac{2-p}{2}}\Big)^{\frac{2}{2-p}}(\|\boldsymbol{h}_{\max(dk)}+\boldsymbol{h}^{(1)}\|_2^2)^{\frac{p}{2-p}}
\end{aligned}$$

$$= \Theta\mu^{\frac{2-2p}{2-p}}\|\boldsymbol{h}_{\max(dk)} + \boldsymbol{h}^{(1)}\|_2^2, \tag{4.24}$$

where the equality is due to (3.4) and

$$\mu = \frac{\|\boldsymbol{h}^{(2)}\|_2^2}{\|\boldsymbol{h}_{\max(dk)} + \boldsymbol{h}^{(1)}\|_2^2}. \tag{4.25}$$

We have $0 \le \mu \le 1$ since

$$\begin{aligned}
\|\boldsymbol{h}^{(2)}\|_2^2 \le & \|\boldsymbol{h}^{(2)}\|_\infty^{2-p}\|\boldsymbol{h}^{(2)}\|_p^p \\
\le & \|\boldsymbol{h}^{(2)}\|_\infty^{2-p}\|\boldsymbol{h}_{\max(dk)} + \boldsymbol{h}^{(1)}\|_p^p \\
\le & \min_{i\in \operatorname{supp}(\boldsymbol{h}_{\max(dk)}+\boldsymbol{h}^{(1)})} |h_i|^{2-p}\|\boldsymbol{h}_{\max(dk)} + \boldsymbol{h}^{(1)}\|_p^p \\
\le & \|\boldsymbol{h}_{\max(dk)} + \boldsymbol{h}^{(1)}\|_2^2,
\end{aligned}$$

where the second inequality is from (4.14), $|T| \le k \le dk$ with $d \ge 1$.

For $\eta \in \mathbb{R}$, let

$$\boldsymbol{\theta_i} = \boldsymbol{h}_{\max(dk)} + \boldsymbol{h}^{(1)} + \eta \boldsymbol{u_i},$$

then

$$\begin{aligned}
\sum_j \lambda_j \boldsymbol{\theta_j} - \frac{p}{2}\boldsymbol{\theta_i} =& \Big(1-\frac{p}{2}\Big)(\boldsymbol{h}_{\max(dk} + \boldsymbol{h}^{(1)}) + \eta\sum_j \lambda_j \boldsymbol{u_j} - \frac{p}{2}\eta \boldsymbol{u_i} \\
\overset{\text{(a)}}{=}& \Big(1-\frac{p}{2}\Big)(\boldsymbol{h}_{\max(dk)} + \boldsymbol{h}^{(1)}) + \eta \boldsymbol{h}^{(2)} - \frac{p}{2}\eta \boldsymbol{u_i} \\
\overset{\text{(b)}}{=}& \Big(1-\frac{p}{2}-\eta\Big)(\boldsymbol{h}_{\max(dk)} + \boldsymbol{h}^{(1)}) + \eta \boldsymbol{h} - \frac{p}{2}\eta \boldsymbol{u_i},
\end{aligned} \tag{4.26}$$

i.e.,

$$\sum_j \lambda_j \boldsymbol{\theta_j} - \frac{p}{2}\boldsymbol{\theta_i} - \eta \boldsymbol{h} = \Big(1-\frac{p}{2}-\eta\Big)\Big(\boldsymbol{h}_{\max(dk)} + \boldsymbol{h}^{(1)}\Big) - \frac{p}{2}\eta \boldsymbol{u_i},$$

where (a) is due to $\boldsymbol{h}^{(2)} = \sum_i \lambda_i \boldsymbol{u_i}$, and (b) is from

$$\boldsymbol{h} = \boldsymbol{h}_{\max(dk)} + \boldsymbol{h}_{\max(dk)^c} \quad \text{and} \quad \boldsymbol{h}_{\max(dk)^c} = \boldsymbol{h}^{(1)} + \boldsymbol{h}^{(2)}.$$

Due to

$$\|\boldsymbol{u_i}\|_0 \le k(t-d) - |\operatorname{supp}(\boldsymbol{h}^{(2)})|$$

and the definition of $\boldsymbol{h}_{\max(dk)}$, the vectors $\boldsymbol{\theta_i}$,

$$\sum_j \lambda_j \boldsymbol{\theta_j} - \frac{p}{2}\boldsymbol{\theta_i} - \eta \boldsymbol{h} \quad \text{and} \quad \Big(1-\frac{p}{2}-\eta\Big)(\boldsymbol{h}_{\max(dk)} + \boldsymbol{h}^{(1)}) - \frac{p}{2}\eta \boldsymbol{u_i}$$

are all tk-sparse. By (4.11) and (4.26), we have

$$\begin{aligned}
&\sum_i \lambda_i \Big\| \mathbf{\Phi}\Big(\sum_j \lambda_j \boldsymbol{\theta}_j - \frac{p}{2}\boldsymbol{\theta}_i \Big) \Big\|_2^2 \\
=&\sum_i \lambda_i \Big\| \mathbf{\Phi}\Big(\Big(1-\frac{p}{2}-\eta\Big)(\boldsymbol{h}_{\max(dk)}+\boldsymbol{h}^{(1)}) - \frac{p}{2}\eta \boldsymbol{u}_i \Big) \Big\|_2^2 \\
\le&(1+\delta_{tk}) \sum_i \lambda_i \Big\| \Big(1-\frac{p}{2}-\eta\Big)(\boldsymbol{h}_{\max(dk)}+\boldsymbol{h}^{(1)}) - \frac{p}{2}\eta \boldsymbol{u}_i \Big\|_2^2 \\
=&(1+\delta_{tk}) \Big[\Big(1-\frac{p}{2}-\eta\Big)^2 \|\boldsymbol{h}_{\max(dk)}+\boldsymbol{h}^{(1)}\|_2^2 + \frac{p^2\eta^2}{4} \sum_i \lambda_i \|\boldsymbol{u}_i\|_2^2 \Big],
\end{aligned} \tag{4.27}$$

where the first inequality is from

$$\Big(1-\frac{p}{2}-\eta\Big)(\boldsymbol{h}_{\max(dk)}+\boldsymbol{h}^{(1)}) - \frac{p}{2}\eta \boldsymbol{u}_i$$

is tk-sparse and the last equality is due to (4.21). Since $\boldsymbol{\theta}_i$ is a tk-sparse vectors, we have

$$\begin{aligned}
&\frac{1-p}{2} \sum_{i,j} \lambda_i \lambda_j \|\mathbf{\Phi}(\boldsymbol{\theta}_i - \boldsymbol{\theta}_j)\|_2^2 \\
=&\eta^2 \frac{1-p}{2} \sum_{i,j} \lambda_i \lambda_j \|\mathbf{\Phi}(\boldsymbol{u}_i - \boldsymbol{u}_j)\|_2^2 \\
\le&(1+\delta_{tk})\eta^2 \frac{1-p}{2} \sum_{i,j} \lambda_i \lambda_j \|\boldsymbol{u}_i - \boldsymbol{u}_j\|_2^2 \\
=&(1+\delta_{tk})\eta^2(1-p) \Big(\sum_i \lambda_i \|\boldsymbol{u}_i\|_2^2 - \Big\| \sum_i \lambda_i \boldsymbol{u}_i \Big\|_2^2 \Big) \\
=&(1+\delta_{tk})\eta^2(1-p) \Big(\sum_i \lambda_i \|\boldsymbol{u}_i\|_2^2 - \|\boldsymbol{h}^{(2)}\|_2^2 \Big),
\end{aligned} \tag{4.28}$$

where the inequality is from that $\boldsymbol{u}_i$ is $(k(t-d)-m)$-sparse and $d<t\le 2d$. $\boldsymbol{u}_i-\boldsymbol{u}_j$ is tk-sparse as $d<t\le 2d$ since

$$tk - 2(k(t-d)-m) = k(2d-t) + m \ge 0.$$

Since $\boldsymbol{\theta}_i$ is tk-sparse, it follows that

$$\begin{aligned}
&\Big(1-\frac{p}{2}\Big)^2 \sum_i \lambda_i \|\mathbf{\Phi}\boldsymbol{\theta}_i\|_2^2 \ge (1-\delta_{tk})\Big(1-\frac{p}{2}\Big)^2 \sum_i \lambda_i \|\boldsymbol{\theta}_i\|_2^2 \\
=&(1-\delta_{tk})\Big(1-\frac{p}{2}\Big)^2 \Big(\|\boldsymbol{h}_{\max(dk)}+\boldsymbol{h}^{(1)}\|_2^2 + \eta^2 \sum_i \lambda_i \|\boldsymbol{u}_i\|_2^2 \Big),
\end{aligned} \tag{4.29}$$

where the equality is from the definition of $\boldsymbol{\theta}_i$ and (4.21).

By (4.27)-(4.29) and the following identity (see [21, (21)])

$$\sum_i \lambda_i \Big\| \boldsymbol{\Phi}\Big(\sum_j \lambda_j \boldsymbol{\theta_j} - \frac{p}{2}\boldsymbol{\theta_i}\Big)\Big\|_2^2 + \frac{1-p}{2}\sum_{i,j}\lambda_i\lambda_j \|\boldsymbol{\Phi}(\boldsymbol{\gamma_i} - \boldsymbol{\theta_j})\|_2^2 - \Big(1-\frac{p}{2}\Big)^2 \sum_i \lambda_i \|\boldsymbol{\Phi}\boldsymbol{\theta}_i\|_2^2 = 0, \tag{4.30}$$

we have

$$\begin{aligned} 0 \leq &(1+\delta_{tk})\Big[\Big(1-\frac{p}{2}-\eta\Big)^2 \|\boldsymbol{h}_{\max(dk)} + \boldsymbol{h}^{(1)}\|_2^2 \\ &+ \eta^2\Big(\frac{p^2}{4} + (1-p)\Big)\sum_i \lambda_i \|\boldsymbol{u_i}\|_2^2 - \eta^2(1-p)\|\boldsymbol{h}^{(2)}\|_2^2\Big] \\ &- (1-\delta_{tk})\Big(1-\frac{p}{2}\Big)^2\Big(\|\boldsymbol{h}_{\max(dk)} + \boldsymbol{h}^{(1)}\|_2^2 + \eta^2 \sum_i \lambda_i \|\boldsymbol{u_i}\|_2^2\Big) \\ =&(1+\delta_{tk})\Big[\Big(1-\frac{p}{2}-\eta\Big)^2 \|\boldsymbol{h}_{\max(dk)} + \boldsymbol{h}^{(1)}\|_2^2 - \eta^2(1-p)\|\boldsymbol{h}^{(2)}\|_2^2\Big] \\ &- (1-\delta_{tk})\Big(1-\frac{p}{2}\Big)^2 \|\boldsymbol{h}_{\max(dk)} + \boldsymbol{h}^{(1)}\|_2^2 \\ &+ 2\delta_{tk}\Big(1-\frac{p}{2}\Big)^2 \eta^2 \sum_i \lambda_i \|\boldsymbol{u_i}\|_2^2. \end{aligned}$$

From (4.25), (4.24) and the above inequality, it follows that

$$\begin{aligned} 0 \leq &\bigg((1+\delta_{tk})\Big(\Big(1-\frac{p}{2}-\eta\Big)^2 - \eta^2(1-p)\mu\Big) - (1-\delta_{tk})\Big(1-\frac{p}{2}\Big)^2 \\ &+ 2\delta_{tk}\Big(1-\frac{p}{2}\Big)^2 \eta^2 \Theta \mu^{\frac{2-2p}{2-p}}\bigg) \|\boldsymbol{h}_{\max(dk)} + \boldsymbol{h}^{(1)}\|_2^2 \\ =&\bigg[(\eta^2 - (2-p)\eta - \eta^2(1-p)\mu) + \delta_{tk}\Big(\Big(1-\frac{p}{2}-\eta\Big)^2 + \Big(1-\frac{p}{2}\Big)^2 \\ &+ 2\Big(1-\frac{p}{2}\Big)^2 \eta^2 \Theta \mu^{\frac{2-2p}{2-p}} - \eta^2(1-p)\mu\Big)\bigg] \|\boldsymbol{h}_{\max(dk)} + \boldsymbol{h}^{(1)}\|_2^2. \end{aligned} \tag{4.31}$$

Next, let the arbitrary vector η satisfies

$$\eta = \frac{2-p}{\sqrt{(1-(1-p)\mu)^2 + (2-p)^2\Theta\mu^{\frac{2-2p}{2-p}}} + 1 - (1-p)\mu}. \tag{4.32}$$

By $0 < p \leq 1$ and $0 \leq \mu \leq 1$, it is clear that $0 < \eta < \frac{2-p}{1-(1-p)\mu}$. Moreover, we have

$$\begin{aligned} \eta^2 - (2-p)\eta - \eta^2(1-p)\mu =&\eta^2\Big(1-(1-p)\mu - (2-p)\frac{1}{\eta}\Big) \\ \overset{(a)}{=}& -\eta^2\sqrt{(1-(1-p)\mu)^2 + (2-p)^2\Theta\mu^{\frac{2-2p}{2-p}}} \end{aligned}$$

and

$$\begin{aligned}&\Big(1-\frac{p}{2}-\eta\Big)^2+\Big(1-\frac{p}{2}\Big)^2+2\Big(1-\frac{p}{2}\Big)^2\eta^2\Theta\mu^{\frac{2-2p}{2-p}}-\eta^2(1-p)\mu\\
=&\eta^2\Big(1-(1-p)\mu+\frac{1}{2}(2-p)^2\Theta\mu^{\frac{2-2p}{2-p}}+\frac{(2-p)^2}{2\eta^2}-(2-p)\frac{1}{\eta}\Big)\\
\overset{(b)}{=}&\eta^2\Big(1-(1-p)\mu+\frac{1}{2}(2-p)^2\Theta\mu^{\frac{2-2p}{2-p}}+\frac{1}{2}\Big(\sqrt{(1-(1-p)\mu)^2+(2-p)^2\Theta\mu^{\frac{2-2p}{2-p}}}\\
&\quad+1-(1-p)\mu\Big)^2-\Big(\sqrt{(1-(1-p)\mu)^2+(2-p)^2\Theta\mu^{\frac{2-2p}{2-p}}}+1-(1-p)\mu\Big)\Big)\\
=&\eta^2\sqrt{(1-(1-p)\mu)^2+(2-p)^2\Theta\mu^{\frac{2-2p}{2-p}}}\Big(\sqrt{(1-(1-p)\mu)^2+(2-p)^2\Theta\mu^{\frac{2-2p}{2-p}}}-(1-p)\mu\Big),\end{aligned}$$

where (a) and (b) are from (4.32). Therefore, from (4.31), it follows that

$$\begin{aligned}&-\eta^2\sqrt{(1-(1-p)\mu)^2+(2-p)^2\Theta\mu^{\frac{2-2p}{2-p}}}\Big[1-\delta_{tk}\Big(\sqrt{(1-(1-p)\mu)^2+(2-p)^2\Theta\mu^{\frac{2-2p}{2-p}}}\\
&\quad-(1-p)\mu\Big)\Big]\|\boldsymbol{h}_{\max(dk)}+\boldsymbol{h}^{(1)}\|_2^2\geq 0.\end{aligned}\tag{4.33}$$

Define a function

$$f(\mu)=\sqrt{(1-(1-p)\mu)^2+(2-p)^2\Theta\mu^{\frac{2-2p}{2-p}}}-(1-p)\mu,$$

where $0\leq\mu\leq 1$. If $\Theta=0$, then $f(\mu)=1-2(1-p)\mu\leq 1$. In this case, (4.33) is a contradiction from $\delta_{tk}<1$. In the following, we assume that $\Theta>0$. By some elementary calculation, we have

$$\begin{aligned}f'(\mu)=&\frac{-2(1-p)(2-p)\Theta\mu^{-\frac{2p}{2-p}}}{\sqrt{(1-(1-p)\mu)^2+(2-p)^2\Theta\mu^{\frac{2-2p}{2-p}}}}\\
&\cdot\Big[\frac{\frac{p}{2}\mu^{\frac{p}{2-p}\frac{2}{p}}+\mu^{\frac{p}{2-p}}-\frac{2-p}{2}\Theta}{(-1+(1-p)\mu)+(2-p)\Theta\mu^{\frac{-p}{2-p}}+\sqrt{(1-(1-p)\mu)^2+(2-p)^2\Theta\mu^{\frac{2-2p}{2-p}}}}\Big]\\
=&\frac{-2(1-p)(2-p)\Theta\mu^{-\frac{2p}{2-p}}}{\sqrt{(1-(1-p)\mu)^2+(2-p)^2\Theta\mu^{\frac{2-2p}{2-p}}}}\\
&\cdot\Big[\frac{g(\mu^{\frac{p}{2-p}})}{(-1+(1-p)\mu)+(2-p)\Theta\mu^{\frac{-p}{2-p}}+\sqrt{(1-(1-p)\mu)^2+(2-p)^2\Theta\mu^{\frac{2-2p}{2-p}}}}\Big],\end{aligned}$$

where

$$g(z)=\frac{p}{2}z^{\frac{2}{p}}+z-\frac{2-p}{2}\Theta.$$

We will use Lemma 4.4 with $z=\mu^{\frac{p}{2-p}}$ to analyze the extreme value of $g(z)$ according to the value of Θ.

(I) For $0<\Theta<\frac{2+p}{2-p}$, by Lemma 4.4 with $z=\mu^{\frac{p}{2-p}}$, a unique point

$$z_0\in\Big((1-p)\Theta,\min\Big(\Big(1-\frac{p}{2}\Big)\Theta,1\Big)\Big)$$

satisfies

$$\begin{cases} g(z)<0, & 0\le z<z_0,\\ g(z)=0, & z=z_0,\\ g(z)>0, & z_0<z\le 1,\end{cases}$$

which implies that

$$\begin{cases} f'(\mu)>0, & 0\le \mu<z_0^{\frac{2-p}{p}},\\ f'(\mu)=0, & \mu=z_0^{\frac{2-p}{p}},\\ f'(\mu)>0, & z_0^{\frac{2-p}{p}}<\mu\le 1.\end{cases}$$

Therefore, when $\mu=z_0^{\frac{2-p}{p}}$, the function $f(\mu)$ achieves its maximal value that

$$\begin{aligned} f(z_0^{\frac{2-p}{p}}) &=\sqrt{\Big(1-(1-p)z_0^{\frac{2-p}{p}}\Big)^2+(2-p)^2\Theta\Big(z_0^{\frac{2-p}{p}}\Big)^{\frac{2-2p}{2-p}}}-(1-p)z_0^{\frac{2-p}{p}}\\ &=\frac{(2-p)\Theta-z_0}{z_0}. \end{aligned} \tag{4.34}$$

By (3.5), (4.34) and (4.33), there is a contradiction under the hypothesis

$$\|\boldsymbol{h}_{\max(dk)}+\boldsymbol{h}^{(1)}\|_2\neq 0.$$

Then

$$\boldsymbol{h}_{\max(dk)}+\boldsymbol{h}^{(1)}=\mathbf{0}.$$

Due to the definition of $\boldsymbol{h}_{\max(dk)}+\boldsymbol{h}^{(1)}$, we have

$$\boldsymbol{h}=\mathbf{0}.$$

(II) For $\Theta\ge\frac{2+p}{2-p}$, by Lemma 4.4 with $z=\mu^{\frac{p}{2-p}}$, $g(z)<0$ for $0\le\mu<1$, which means that $f'(\mu)>0$. Therefore, when $\mu=1$, $f(\mu)$ achieves its maximal value that

$$f_{\max}(1)=\sqrt{p^2+(2-p)^2\Theta}-(1-p). \tag{4.35}$$

By (3.5), (4.35) and (4.33), there is a contradiction under the hypothesis

$$\|\boldsymbol{h}_{\max(dk)}+\boldsymbol{h}^{(1)}\|\neq 0.$$

Then

$$\boldsymbol{h}_{\max(dk)}+\boldsymbol{h}^{(1)}=\mathbf{0}.$$

Due to the definition of $\boldsymbol{h}_{\max(dk)}+\boldsymbol{h}^{(1)}$, we have $\boldsymbol{h}=\mathbf{0}$. In conclusion, we complete the proof of Theorem 3.1. □

4.3 Proof of Corollary 3.1

Proof. By $p=1$ and (3.4),

$$\begin{aligned}\Theta =&(t-d)^{-1}\Big(\omega_L+(1-\omega_1)\Big(1+\sum_{j=1}^{L}\rho_j-2\sum_{j=1}^{L}\alpha_j\rho_j\Big)^{\frac{2-p}{2}}\\&+\sum_{i=2}^{L}(\omega_{i-1}-\omega_i)\Big(1+\sum_{j=1}^{L}\rho_j-2\sum_{j=1}^{L}\alpha_j\rho_j\Big)^{\frac{2-p}{2}}\Big)^2.\end{aligned}$$

On one hand, the only positive solution z_0 of Eq. (3.6) with $p=1$ is $-1+\sqrt{1+\Theta}$.

From $p=1$ and $z_0=-1+\sqrt{1+\Theta}$, it follows that

$$\frac{z_0}{(2-p)\Theta-z_0}=\frac{-1+\sqrt{1+\Theta}}{\Theta-(-1+\sqrt{1+\Theta})}=\frac{1}{\sqrt{1+\Theta}}.$$

On the other hand, for $p=1$,

$$\frac{1}{\sqrt{p^2+(2-p)^2\Theta}-(1-p)}=\frac{1}{\sqrt{1+\Theta}}.$$

By Theorem 3.1, the condition (3.7) guarantees the exact recovery of x. □

4.4 Proof of Theorem 3.2

Proof. Theorem 3.2 can be proved by following the routine proofs of Theorem III.10 in [9] and Theorem 3.1 in this paper. We omit the details. □

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