On the Null Space Constant for ℓ_p Minimization

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Abstract—The literature on sparse recovery often adopts the ℓ_p "norm" ($p \in [0, 1]$) as the penalty to induce sparsity of the signal satisfying an underdetermined linear system. The performance of the corresponding ℓ_p minimization problem can be characterized by its null space constant. In spite of the NP-hardness of computing the constant, its properties can still help in illustrating the performance of ℓ_p minimization. In this letter, we show the strict increase of the null space constant in the sparsity level k and its continuity in the exponent p. We also indicate that the constant is strictly increasing in p with probability 1 when the sensing matrix A is randomly generated. Finally, we show how these properties can help in demonstrating the performance of ℓ_p minimization, mainly in the relationship between the the exponent p and the sparsity level k.

Index Terms—Continuity, ℓ_p minimization, monotonicity, null space constant, sparse recovery.

I. INTRODUCTION

N IMPORTANT problem that often arises in signal processing, machine learning, and statistics is sparse recovery [1]–[3]. It is in general formulated in the standard form

$$\underset{\mathbf{x}}{\arg\min} \|\mathbf{x}\|_{0} \quad \text{subject to} \quad \mathbf{A}\mathbf{x} = \mathbf{y} \tag{1}$$

where the sensing matrix $\mathbf{A} \in \mathbb{R}^{M \times N}$ has more columns than rows and the ℓ_0 "norm" $\|\mathbf{x}\|_0$ denotes the number of nonzero entries of the vector \mathbf{x} . The combinatorial optimization (1) is NP-hard and therefore cannot be solved efficiently [4]. A standard method to solve this problem is by relaxing the non-convex discontinuous ℓ_0 "norm" to the convex ℓ_1 norm [5], i.e.,

$$\underset{\mathbf{x}}{\operatorname{arg\,min}} \|\mathbf{x}\|_{1} \quad \text{subject to} \quad \mathbf{A}\mathbf{x} = \mathbf{y}. \tag{2}$$

It is theoretically proved that under some certain conditions [5], [6], the optimum solution of (2) is identical to that of (1).

Some works try to bridge the gap between ℓ_0 "norm" and ℓ_1 norm by non-convex but continuous ℓ_p "norm" ($0) [7]–[10], and consider the <math>\ell_p$ minimization problem

$$\underset{\mathbf{x}}{\arg\min} \|\mathbf{x}\|_{p}^{p} \quad \text{subject to} \quad \mathbf{A}\mathbf{x} = \mathbf{y} \tag{3}$$

where $\|\mathbf{x}\|_p^p = \sum_{i=1}^N |x_i|^p$. Though finding the global optimal solution of ℓ_p minimization is still NP-hard, computing a local

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minimizer can be done in polynomial time [11]. The global optimality of (3) has been studied and various conditions have been derived, for example, those based on restricted isometry property [7]–[9], [12] and null space property [10], [13]. Among them, a necessary and sufficient condition is based on the null space property and its constant [10], [13], [14].

Definition 1: For any $0 \le p \le 1$, define null space constant $\gamma(\ell_p, \mathbf{A}, k)$ as the smallest quantity such that

$$\sum_{i \in S} |z_i|^p \le \gamma(\ell_p, \mathbf{A}, k) \sum_{i \notin S} |z_i|^p \tag{4}$$

holds for any set $S \subset \{1, 2, ..., N\}$ with $\#S \leq k$ and for any vector $\mathbf{z} \in \mathcal{N}(\mathbf{A})$ which denotes the null space of \mathbf{A} .

It has been shown that for any $p \in [0, 1]$, $\gamma(\ell_p, \mathbf{A}, k) < 1$ is a necessary and sufficient condition such that for any k-sparse \mathbf{x}^* and $\mathbf{y} = \mathbf{A}\mathbf{x}^*, \mathbf{x}^*$ is the unique solution of ℓ_p minimization [10]. Therefore, $\gamma(\ell_p, \mathbf{A}, k)$ is a tight quantity in indicating the performance of ℓ_p minimization $(0 \le p \le 1)$ in sparse recovery. However, it has been shown that calculating $\gamma(\ell_p, \mathbf{A}, k)$ is in general NP-hard [15], which makes it difficult to check whether the condition is satisfied or violated. Despite this, properties of $\gamma(\ell_p, \mathbf{A}, k)$ are of tremendous help in illustrating the performance of ℓ_p minimization, e.g., non-decrease of $\gamma(\ell_p, \mathbf{A}, k)$ in $p \in [0, 1]$ shows that if ℓ_p minimization guarantees successful recovery of all k-sparse signal and $0 \le q \le p$, then ℓ_q minimization also does [10].

In this letter, we give some new properties of the null space constant $\gamma(\ell_p, \mathbf{A}, k)$. Specifically, we prove that $\gamma(\ell_p, \mathbf{A}, k)$ is strictly increasing in k and is continuous in p. For random sensing matrix **A**, the non-decrease of $\gamma(\ell_p, \mathbf{A}, k)$ in p can be improved to strict increase with probability 1. Based on them, the performance of ℓ_p minimization can be intuitively demonstrated and understood.

II. MAIN CONTRIBUTION

This section introduces some properties of null space constant $\gamma(\ell_p, \mathbf{A}, k)(0 \le p \le 1)$. We begin with a lemma about $\gamma(\ell_p, \mathbf{A}, k)$ which will play a central role in the theoretical analysis. The spark of a matrix \mathbf{A} , denoted as Spark(\mathbf{A})[16], is the smallest number of columns from \mathbf{A} that are linearly dependent.

- Lemma 1: Suppose Spark(\mathbf{A}) = L + 1. For $p \in [0, 1]$,
- 1) $\gamma(\ell_p, \mathbf{A}, k)$ is finite if and only if $k \leq L$;
- 2) For $k \leq L$, there exist $S' \subset \{1, 2, ..., N\}$ with $\#S' \leq k$ and $\mathbf{z}' \in \mathcal{N}(\mathbf{A}) \setminus \{\mathbf{0}\}$ such that

$$\sum_{i \in S'} |z'_i|^p = \gamma(\ell_p, \mathbf{A}, k) \sum_{i \notin S'} |z'_i|^p \tag{5}$$

Proof: See Section III-A.

First, we show the strict increase of $\gamma(\ell_p, \mathbf{A}, k)$ in k.

Theorem 1: Suppose Spark(\mathbf{A}) = L+1. Then for $p \in [0, 1]$, $\gamma(\ell_p, \mathbf{A}, k)$ is strictly increasing in k when $k \leq L$.

Proof: See Section III-B.

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Remark 1: For any $p \in [0, 1]$, we can define a set $\mathcal{K}_p(\mathbf{A})$ of all positive integers k that every k-sparse \mathbf{x}^* can be recovered as the unique solution of ℓ_p minimization (3) with $\mathbf{y} = \mathbf{A}\mathbf{x}^*$. According to Theorem 1, $\mathcal{K}_p(\mathbf{A})$ contains successive integers starting from 1 to some integer $k_p^*(\mathbf{A})$ and is possibly empty.

Remark 2: If Spark(\mathbf{A}) = L + 1, then $k_0^*(\mathbf{A}) = \lfloor L/2 \rfloor$ [16]. Therefore, if $L \ge 2$, $k_0^*(\mathbf{A}) \ge 1$.

Remark 3: For **A** with identical column norms, if Spark(**A**) = L + 1 and $L \ge 2$, then $k_1^*(\mathbf{A}) \ge 1$. To show this, we only need to prove that $\gamma(\ell_1, \mathbf{A}, 1) < 1$. First, for any $1 \le i \le N$ and $\mathbf{z} \in \mathcal{N}(\mathbf{A}) \setminus \{\mathbf{0}\}$, since $\mathbf{A}\mathbf{z} = 0$, $z_i \mathbf{a}_i = -\sum_{j \ne i} z_j \mathbf{a}_j$ where \mathbf{a}_i is the *i*th column of **A**. Since

$$|z_i| \cdot ||\mathbf{a}_i||_2 = ||z_i\mathbf{a}_i||_2 = ||\sum_{j \neq i} z_j\mathbf{a}_j||_2 \le \sum_{j \neq i} |z_j| \cdot ||\mathbf{a}_j||_2$$

with equality holds only when $z_j \mathbf{a}_j (j \neq i)$ are all on the same ray, which cannot be true since $\text{Spark}(\mathbf{A}) = L + 1 \ge 3$. Since **A** has identical column norms, $|z_i| < \sum_{j \neq i} |z_j|$ holds, which leads to $\gamma(\ell_1, \mathbf{A}, 1) < 1$ because of Lemma 1.2).

Now we turn to the properties of $\gamma(\ell_p, \mathbf{A}, k)$ as a function of p. The following result reveals the continuity of $\gamma(\ell_p, \mathbf{A}, k)$ in p.

Theorem 2: Suppose Spark(\mathbf{A}) = L + 1. Then for $k \leq L$, $\gamma(\ell_p, \mathbf{A}, k)$ is a continuous function in $p \in [0, 1]$.

Proof: See Section III-C.

Remark 4: Some works have discussed the equivalence of ℓ_0 and ℓ_p minimizations. In [17], it is shown that the sufficient condition for the equivalence of these two minimization problems approaches the necessary and sufficient condition for the uniqueness of solutions of ℓ_0 minimization. In [7], it is shown that for any k-sparse \mathbf{x}^* and $\mathbf{y} = \mathbf{A}\mathbf{x}^*$, if $\delta_{2k+1} < 1$, then there is p > 0 such that \mathbf{x}^* is the unique solution of ℓ_p minimization. This result is improved to $\delta_{2k} < 1$ which is optimal since it is exactly the necessary and sufficient condition for \mathbf{x}^* being the unique solution of ℓ_0 minimization [12]. [18] shows the equivalence of the ℓ_0 - and the ℓ_p -norm minimization problem for sufficiently small p. According to Theorem 2, we can also justify this result: For any k-sparse \mathbf{x}^* and $\mathbf{y} = \mathbf{A}\mathbf{x}^*$, if $\gamma(\ell_0, \mathbf{A}, k) < 1$, then there is p > 0 such that $\gamma(\ell_p, \mathbf{A}, k) < 1$ and \mathbf{x}^* is the unique solution of ℓ_p minimization.

Remark 5: In [10], the author defines a set $\mathcal{P}_k(\mathbf{A})$ of reconstruction exponents, that is the set of all exponents $0 for which every k-sparse <math>\mathbf{x}^*$ is recovered as the unique solution of ℓ_p minimization with $\mathbf{y} = \mathbf{A}\mathbf{x}^*$. It is shown that $\mathcal{P}_k(\mathbf{A})$ is a (possibly empty) open interval $(0, p_k^*(\mathbf{A}))[10]$. This result can be easily shown by Theorem 2. Since $\gamma(\ell_p, \mathbf{A}, k)$ is a non-decreasing [13] continuous function in $p \in [0, 1]$, the inverse image of the open interval $(-\infty, 1)$ is also an open interval of [0, 1]. Therefore, the requirement that $\gamma(\ell_p, \mathbf{A}, k) < 1$ is equivalent to $p \in [0, p_k^*(\mathbf{A}))$.

Remark 6: For any **A**, we can plot $k_p^*(\mathbf{A})$ as a function of p, as shown in Fig. 1. For concision, we omit the argument **A** in the figure. It is obvious that $k_p^*(\mathbf{A})$ is a step function decreasing from $k_0^*(\mathbf{A})$ to $k_1^*(\mathbf{A})$. Three facts needs to be pointed out. First, $k_p^*(\mathbf{A})$ is right-continuous, which is an easy consequence of Theorem 2. Second, the points (p_0, k_0) corresponding to the hollow circles in Fig. 1 satisfy $\gamma(\ell_{p_0}, \mathbf{A}, k_0) = 1$. Third, for the *p*-axis p_0 of the points of discontinuity, the one-sided limits satisfy $\lim_{p \to p_0^-} k_p^*(\mathbf{A}) - \lim_{p \to p_0^+} k_p^*(\mathbf{A}) = 1$. This



Fig. 1. The figure shows $k_p^*(\mathbf{A})$ as a function of p, where the argument \mathbf{A} is omitted for concision.



Fig. 2. This figure shows a diagrammatic sketch of $\gamma(\ell_p, \mathbf{A}, k)$ as a function of p for different k when **A** is a random matrix.

can be proved by Theorem 1 that if $\gamma(\ell_{p_0}, \mathbf{A}, k_0) = 1$, then $\gamma(\ell_{p_0}, \mathbf{A}, k_0 - 1) < 1$.

Finally, we introduce an important property of $\gamma(\ell_p, \mathbf{A}, k)$ as a function of p with regard to random matrix \mathbf{A} .

Theorem 3: Suppose the entries of $\mathbf{A} \in \mathbb{R}^{M \times N}$ are i.i.d. and satisfy a continuous probability distribution. Then for $k \leq M$, $\gamma(\ell_p, \mathbf{A}, k)$ is strictly increasing in $p \in [0, 1]$ with probability one.

Proof: See Section III-D.

Remark 7: It needs to be noted that there exists A such that $\gamma(\ell_p, \mathbf{A}, k)$ is a constant number for all $p \in [0, 1]$. For example, for

$$\mathbf{A} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1\\ 1 & 1 \end{bmatrix},\tag{6}$$

Spark(A) = 2. Since $\mathcal{N}(\mathbf{A}) = \text{span}([1, -1]^T)$, it is easy to check that for all $p \in [0, 1]$, $\gamma(\ell_p, \mathbf{A}, 1) = 1$.

Remark 8: To sum up, we can schematically show $\gamma(\ell_p, \mathbf{A}, k)$ as a function of p for different k in Fig. 2. According to Theorem 1, these curves are strictly in order without intersections. Theorem 2 reveals that $\gamma(\ell_p, \mathbf{A}, k)$ is continuous in p. For a random matrix \mathbf{A} with i.i.d. entries satisfying a continuous probability distribution, $\gamma(\ell_p, \mathbf{A}, k)$ is strictly increasing in p with probability 1 by Theorem 3. According to the definition of $k_p^*(\mathbf{A})$, the curves intersecting $\gamma(\ell_p, \mathbf{A}, k) = 1(0 \le p \le 1)$ are those with $k_1^*(\mathbf{A}) + 1 \le k \le k_0^*(\mathbf{A})$. According to the definition of $p_k^*(\mathbf{A})$, the p-axis of these intersections are $p_{k_0^*}^*$, $p_{k_0^*-1}^*, \ldots, p_{k_1^*+1}^*$ from left to right. Therefore, it is easy to derive Fig. 1 based on Fig. 2 when \mathbf{A} is a random matrix.

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III. PROOFS

A. Proof of Lemma 1

Proof: 1) Since Spark(\mathbf{A}) = L + 1, $\mathcal{N}(\mathbf{A})$ contains an (L + 1)-sparse signal, and it is easy to show that for any $k \geq L + 1$, $\gamma(\ell_p, \mathbf{A}, k) = +\infty$ according to Definition 1. Next we prove that for $k \leq L$, $\gamma(\ell_p, \mathbf{A}, k)$ is finite. Define

$$\theta(p, \mathbf{z}, S) = \frac{\sum_{i \in S} |z_i|^p}{\sum_{i \notin S} |z_i|^p} \tag{7}$$

and $\mathcal{N}_1(\mathbf{A}) = \mathcal{N}(\mathbf{A}) \cap \{\mathbf{z} : \|\mathbf{z}\|_2 = 1\}$ which is a compact set. Then it is easy to see that the definition of null space constant is equivalent to

$$\gamma(\ell_p, \mathbf{A}, k) = \max_{\#S \le k} \sup_{\mathbf{z} \in \mathcal{N}_1(\mathbf{A})} \theta(p, \mathbf{z}, S).$$
(8)

If $\gamma(\ell_p, \mathbf{A}, k)$ is not finite, then there exists S' with $\#S' \leq k$ such that $\sup_{\mathbf{z} \in \mathcal{N}_1(\mathbf{A})} \theta(p, \mathbf{z}, S')$ is not finite. Therefore, for any $n \in \mathbb{N}^+$, there exists $\mathbf{z}^{(n)} \in \mathcal{N}_1(\mathbf{A})$ such that

$$\theta(p, \mathbf{z}^{(n)}, S') \ge n. \tag{9}$$

If p = 0, since $\mathbf{z}^{(n)}$ is at least (L + 1)-sparse, it is easy to see that $\theta(0, \mathbf{z}^{(n)}, S') \leq k$ holds for any $n \in \mathbb{N}^+$. This contradicts (9) when n > k. If $p \in (0, 1]$, according to Lemma 4.5 in [10], $\|\mathbf{z}^{(n)}\|_p \leq N^{\frac{1}{p} - \frac{1}{2}} \|\mathbf{z}^{(n)}\|_2 = N^{\frac{1}{p} - \frac{1}{2}}$, and (9) implies

$$\sum_{i \notin S'} |z_i^{(n)}|^p \le \frac{N^{1-\frac{p}{2}}}{n+1}.$$
(10)

Due to the compactness of $\mathcal{N}_1(\mathbf{A})$, the sequence $\{\mathbf{z}^{(n)}\}_n$ has a convergent subsequence $\{\mathbf{z}^{(n_m)}\}_m$, and its limit \mathbf{z}' also lies in $\mathcal{N}_1(\mathbf{A})$. Then (10) implies $z'_i = 0$ for $i \notin S'$, i.e., $\mathcal{N}_1(\mathbf{A})$ contains a k-sparse element \mathbf{z}' . This contradicts the assumption that $\text{Spark}(\mathbf{A}) = L + 1 > k$.

2) If p = 0, for any S with $\#S \le k$ and any $\mathbf{z} \in \mathcal{N}(\mathbf{A}) \setminus \{\mathbf{0}\}$, it holds that

$$\theta(0, \mathbf{z}, S) \le \frac{k}{L+1-k}.$$
(11)

On the other hand, since $\text{Spark}(\mathbf{A}) = L + 1$, $\mathcal{N}(\mathbf{A})$ contains an (L + 1)-sparse signal \mathbf{z}' with T as its support set. For any $S' \subset T$ with #S' = k, $\theta(0, \mathbf{z}', S') = k/(L + 1 - k)$, and therefore (5) holds.

If $p \in (0, 1]$, recalling the equivalent definition (8), there exists S' with $\#S' \leq k$ such that

$$\gamma(\ell_p, \mathbf{A}, k) = \sup_{\mathbf{z} \in \mathcal{N}_1(\mathbf{A})} \theta(p, \mathbf{z}, S').$$
(12)

Since $\mathcal{N}_1(\mathbf{A})$ is compact and the function $\theta(p, \mathbf{z}, S')$ is continuous in \mathbf{z} on $\mathcal{N}_1(\mathbf{A})$, it is easy to show that there exists $\mathbf{z}' \in \mathcal{N}_1(\mathbf{A})$ such that $\gamma(\ell_p, \mathbf{A}, k) = \theta(p, \mathbf{z}', S')$.

B. Proof of Theorem 1

Proof: We prove that when $p \in [0, 1]$ and $2 \le k \le L$,

$$\gamma(\ell_p, \mathbf{A}, k-1) < \gamma(\ell_p, \mathbf{A}, k).$$
(13)

According to Lemma 1.2), there exist S' with $\#S' \le k-1$ and $\mathbf{z}' \in \mathcal{N}_1(\mathbf{A})$ such that

$$\gamma(\ell_p, \mathbf{A}, k-1) = \theta(p, \mathbf{z}', S').$$
(14)

Since \mathbf{z}' is at least (L + 1)-sparse, there exists an index $s' \in \{1, 2, ..., N\} \setminus S'$ such that $z'_{s'} \neq 0$. Let $S'' = S' \cup \{s'\}$, then

$$\sum_{i \in S'} |z'_i|^p < \sum_{i \in S''} |z'_i|^p, \sum_{i \notin S'} |z'_i|^p > \sum_{i \notin S''} |z'_i|^p > 0$$
(15)

and hence

$$\theta(p, \mathbf{z}', S') < \theta(p, \mathbf{z}', S'').$$
(16)

Recalling (14) and the equivalent definition (8), we can get (13) and complete the proof.

C. Proof of Theorem 2

Proof: According to Theorem 5 in [13], $\gamma(\ell_p, \mathbf{A}, k)$ is nondecreasing in $p \in [0, 1]$ and therefore can only have jump discontinuities. We show this is impossible by two steps.

First, for any $p \in (0, 1]$, we prove the one-sided limit from the negative direction satisfies

$$L^{-} := \lim_{q \to p^{-}} \gamma(\ell_q, \mathbf{A}, k) = \gamma(\ell_p, \mathbf{A}, k).$$
(17)

According to Lemma 1.2), there exist S' with $\#S' \leq k$ and $\mathbf{z}' \in \mathcal{N}_1(\mathbf{A})$ satisfying

$$\gamma(\ell_p, \mathbf{A}, k) = \theta(p, \mathbf{z}', S').$$
(18)

According to the definition of $\theta(p, \mathbf{z}, S)$, it is easy to show that

$$\lim_{q \to p^-} \theta(q, \mathbf{z}', S') = \theta(p, \mathbf{z}', S'), \tag{19}$$

and then (17) holds obviously.

Second, for any $p \in [0, 1)$, we prove the one-sided limit from the positive direction satisfies

$$L^{+} := \lim_{q \to p^{+}} \gamma(\ell_{q}, \mathbf{A}, k) = \gamma(\ell_{p}, \mathbf{A}, k).$$
(20)

Since p < 1, there exists $N_0 \in \mathbb{N}^+$ such that $p + N_0^{-1} \leq 1$. Then for $n \geq N_0$, Lemma 1.2) reveals that there exist $S^{(n)}$ with $\#S^{(n)} \leq k$ and $\mathbf{z}^{(n)} \in \mathcal{N}_1(\mathbf{A})$ such that

$$\gamma(\ell_{p+n^{-1}}, \mathbf{A}, k) = \theta(p+n^{-1}, \mathbf{z}^{(n)}, S^{(n)}).$$
(21)

Since there are only finite different S satisfying $\#S \leq k$, there exists S' with $\#S' \leq k$ such that an infinite subsequence of $\{\mathbf{z}^{(n)}\}_n$ is associated with S'. Due to the compactness of $\mathcal{N}_1(\mathbf{A})$, this subsequence has a convergent subsequence $\{\mathbf{z}^{(n_m)}\}_m$, and its limit \mathbf{z}' also lies in $\mathcal{N}_1(\mathbf{A})$. According to the definition of $\theta(p, \mathbf{z}, S)$ and (21),

$$\theta(p, \mathbf{z}', S') = \lim_{m \to +\infty} \theta(p + n_m^{-1}, \mathbf{z}^{(n_m)}, S') = L^+, \quad (22)$$

and consequently $\gamma(\ell_p, \mathbf{A}, k) \ge L^+$. Since $\gamma(\ell_p, \mathbf{A}, k)$ is nondecreasing in $p, \gamma(\ell_p, \mathbf{A}, k) \le L^+$ and (20) is proved.

D. Proof of Theorem 3

Proof: First, we show that $\text{Spark}(\mathbf{A}) = M + 1$ with probability 1. Let $\mathcal{M}(M)$ denote the M^2 -dimensional vector space of $M \times M$ real matrices. For any $0 \leq k \leq M$, let $\mathcal{M}_k(M)$ denote the subset of $\mathcal{M}(M)$ consisting of matrices of rank k. It can be proved that $\mathcal{M}_k(M)$ is an embedded submanifold of dimension k(2M - k) in $\mathcal{M}(M)$ [19]. Consequently, for $M \times M$ matrices with i.i.d. entries drawn from a continuous distribution, the M^2 -dimensional volume of the set of singular matrices $\bigcup_{k=0}^{M-1} \mathcal{M}_k(M)$ is zero. In other words, any M, or fewer,

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random vectors in \mathbb{R}^M with i.i.d. entries drawn from a continuous distribution are linearly independent with probability 1. On the other hand, more than M vectors in \mathbb{R}^M are always linearly dependent. Therefore, $\text{Spark}(\mathbf{A}) = M + 1$ with probability 1.

Next, with the equivalent definition (8), we prove that for $k \le M$ and $0 \le p < q \le 1$,

$$\max_{\#S \le k} \sup_{\mathbf{z} \in \mathcal{N}_1(\mathbf{A})} \theta(p, \mathbf{z}, S) < \max_{\#S \le k} \sup_{\mathbf{z} \in \mathcal{N}_1(\mathbf{A})} \theta(q, \mathbf{z}, S)$$
(23)

holds with probability 1. According to Lemma 1.2), there exist S' with $\#S' \leq k$ and $\mathbf{z}' \in \mathcal{N}_1(\mathbf{A})$ such that

$$\theta(p, \mathbf{z}', S') = \max_{\#S \le k} \sup_{\mathbf{z} \in \mathcal{N}_1(\mathbf{A})} \theta(p, \mathbf{z}, S).$$
(24)

Suppose \mathbf{z}' has N_* nonzero entries with T as its support set, then $N_* \ge M + 1$ with probability 1. It is obvious that $S' \subset T$, and for any $i \in S'$ and any $l \in T \setminus S'$, $|z'_i| \ge |z'_l| > 0$. Since p < q, $|z'_i|^{q-p} \ge |z'_l|^{q-p}$ and therefore

$$|z_i'|^q |z_l'|^p \ge |z_i'|^p |z_l'|^q.$$
(25)

Summing (25) with *i* in S' and *l* in $T \setminus S'$, we can obtain

$$\sum_{i \in S'} |z'_i|^q \sum_{l \in T \setminus S'} |z'_l|^p \ge \sum_{i \in S'} |z'_i|^p \sum_{l \in T \setminus S'} |z'_l|^q \qquad (26)$$

which is equivalent to

$$\theta(p, \mathbf{z}', S') \le \theta(q, \mathbf{z}', S'). \tag{27}$$

Since p < q, it is easy to check that the equality in (27) holds only when $|z'_i| = |z'_i|$ for all $i \in S'$ and all $l \in T \setminus S'$, i.e., the nonzero entries of \mathbf{z}' have the same magnitude. We prove that $\mathcal{N}_1(\mathbf{A})$ contains such \mathbf{z}' with probability 0, which together with (24) imply that

$$\gamma(\ell_p, \mathbf{A}, k) = \theta(p, \mathbf{z}', S') < \theta(q, \mathbf{z}', S') \le \gamma(\ell_q, \mathbf{A}, k) \quad (28)$$

holds with probability 1.

To this end, let $\mathcal{M}(M, N)$ denote the MN-dimensional vector space of $M \times N$ real matrices. For fixed $\mathbf{z} \in \mathbb{R}^N$ with $\|\mathbf{z}\|_2 = 1$, it can be easily shown that the subset

$$\mathcal{M}_{\mathbf{z}}(M,N) = \{ \mathbf{A} \in \mathcal{M}(M,N) : \mathbf{A}\mathbf{z} = \mathbf{0} \}$$
(29)

is an M(N-1)-dimensional subspace in $\mathcal{M}(M, N)$. Therefore, for $\mathbf{A} \in \mathcal{M}(M, N)$ with i.i.d. entries drawn from a continuous probability distribution, $\mathcal{N}_1(\mathbf{A})$ contains \mathbf{z} with probability 0. In $\{\mathbf{z} \in \mathbb{R}^N : ||\mathbf{z}||_2 = 1\}$, the number of vectors whose nonzero entries have the same magnitude is

$$\sum_{i=1}^{N} \binom{N}{i} 2^{i} = 3^{N} - 1 \tag{30}$$

which is a finite number. Therefore, with probability 0, $\mathcal{N}_1(\mathbf{A})$ contains a vector \mathbf{z}' which makes the equality in (27) hold. That is, $\gamma(\ell_p, \mathbf{A}, k)$ is strictly increasing in $p \in [0, 1]$ with probability 1.

IV. CONCLUSION

In characterizing the performance of ℓ_p minimization in sparse recovery, null space constant $\gamma(\ell_p, \mathbf{A}, k)$ can be served as a necessary and sufficient condition for the perfect recovery of all k-sparse signals. This letter derives some basic properties of $\gamma(\ell_p, \mathbf{A}, k)$ in k and p. In particular, we show that $\gamma(\ell_p, \mathbf{A}, k)$ is strictly increasing in k and is continuous in p, meanwhile for random \mathbf{A} , the constant is strictly increasing in p with probability 1. Possible future works include the properties of $\gamma(\ell_p, \mathbf{A}, k)$ in \mathbf{A} , for example, the requirement of number of measurements M to guarantee $\gamma(\ell_p, \mathbf{A}, k) < 1$ with high probability when \mathbf{A} is randomly generated.

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