On Sparse Representation in Pairs of Bases

Arie Feuer, Senior Member, IEEE, and Arkadi Nemirovski

Abstract—In previous work, Elad and Bruckstein (EB) have provided a sufficient condition for replacing an l_0 optimization by linear programming minimization when searching for the unique sparse representation. We establish here that the EB condition is both sufficient and necessary.

Index Terms—Dictionary, sparse representation, tight frame.

I. INTRODUCTION

In their recent publication, [1], Elad and Bruckstein (EB) address the following problem:

Given two orthogonal matrices Φ , $\Psi \in \mathbb{R}^{N \times N}$ and a vector $\underline{S} \in \mathbb{R}^{N}$ consider the following two optimization problems:

 (P_0) Minimize

$$\left\|\underline{\gamma}\right\|_{0} = \sum_{k=1}^{2N} \gamma_{k}^{0}$$

subject to

$$\underline{S} = [\Phi, \Psi] \underline{\gamma}$$

and (P_1) Minimize

$$\left\|\underline{\gamma}\right\|_1 = \sum_{k=1}^{2N} |\gamma_k|$$

subject to

 $\underline{S} = [\Phi, \Psi] \gamma$

where by $\|\gamma\|_0$ we refer to the number of nonzero entries of vector γ .

The columns of each matrix Φ , Ψ constitute an orthonormal basis in \mathbb{R}^N . When viewed together as a set of 2N vectors they are referred to in [1] as a dictionary (we also note that this set of vectors is in fact a tight frame with frame bound 2). The vector $\underline{\gamma} \in \mathbb{R}^{2N}$ is a representation of vector (signal) \underline{S} in this dictionary. A question of obvious interest is what can be gained by representing \underline{S} in the dictionary rather than in either basis. The answer lies in the possibility of getting sparser representations where the measure of sparseness is the norm $\|\cdot\|_0$ (which just counts the nonzero entries of the vector). Clearly, one can always find $\underline{\gamma}$ so that $\|\underline{\gamma}\|_0 \leq \min\{\|\underline{\alpha}\|_0, \|\underline{\beta}\|_0\}$ where $\underline{S} = \Phi \underline{\alpha} = \Psi \underline{\beta}$ (note that $[\frac{\alpha}{0}]$ and $[\frac{0}{\underline{\beta}}]$ are also representations of the signal in the dictionary). Hence, problem (P_0) is in fact an attempt to find the sparsest representation of a given vector (signal) in a particular dictionary—this is of much interest in, e.g., signal compression problems.

In [1], the following result on the uniqueness of this representation is given.

Theorem 1 [1, Theorem 2]: Let

$$M = \max_{1 \le i, j \le N} \left(\left| \left\langle \underline{\phi}_{i}, \underline{\psi}_{j} \right\rangle \right| \right)$$
(1)

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A. Feuer is with the Control and Robotics Laboratory, Department of Electrical Engineering, Technion–Israel Institute of Technology, 32000 Technion City, Haifa, Israel (e-mail: feuer@ee.technion.ac.il).

A. Nemirovsky is with the Department of Industrial Engineering and Management, Technion–Israel Institute of Technology, 32000 Technion City, Haifa, Israel (e-mail: nemitovs@ie.technion.ac.il).

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$$\left\|\underline{\gamma}_{1}\right\|_{0}+\left\|\underline{\gamma}_{2}\right\|_{0}\geq\frac{2}{M}.$$
(2)

This means that the uniqueness of a sparse representation is ensured by

$$\left\|\underline{\gamma}\right\|_0 < \frac{1}{M}.\tag{3}$$

Clearly, condition (3) guarantees the uniqueness of the solution of problem (P_0) . However, finding this representation, namely, solving (P_0) is a problem we do not know how to solve efficiently. As pointed out in [2], under certain conditions, solving (P_0) can be traded with solving (P_1) a much easier problem. The sufficient condition found by Donoho and Huo is that if

$$\left\|\underline{\gamma}\right\|_{0} < \frac{1}{2} \left(1 + \frac{1}{M}\right) \tag{4}$$

then (P_0) and (P_1) are equivalent problems in the sense that the (unique) solution of (P_1) is also the (unique) solution of (P_0) .

In [1], this condition is relaxed and a higher bound is given, again, as a sufficient condition

$$\left\|\underline{\gamma}\right\|_{0} < \frac{\sqrt{2} - 0.5}{M}.$$
(5)

We are going to show that the condition in (5) is in fact both necessary and sufficient. So, this bound for the equivalency of problems (P_0) and (P_1) is tight.

II. MAIN RESULT

In this section, we are going to show that the bound presented in [1] is tight. To do that we first prove the following proposition.

Proposition 2: Let $L_0 < \frac{1}{M}$ be a given integer and

$$\Theta_{L_0}\left(\underline{x}\right) = \frac{S_{L_0}\left(\underline{x}\right)}{\|\underline{x}\|_1} \tag{6}$$

where $S_{L_0}(\underline{x})$ is the sum of the L_0 largest absolute values of the entries of $\underline{x} \in \mathbb{R}^{2N}$. Then, (P_0) and (P_1) are equivalent if and only if

$$\sup_{[\Phi, \Psi]\underline{x}=0} \Theta_{L_0}(\underline{x}) < \frac{1}{2}.$$
(7)

Proof: Note that in the proof here we use Theorem 1 implicitly, claiming that since $L_0 < \frac{1}{M}$, $\underline{\gamma}$ is indeed the unique solution of (P_0) for $\underline{S} = [\Phi, \Psi] \gamma$.

Suppose (7) holds. Then for any $\underline{\gamma}, \ \underline{\tilde{\gamma}} \in \mathbb{R}^{2N}$ such that $\|\underline{\gamma}\|_0 = L_0$ and $[\Phi, \Psi] \ \gamma = [\Phi, \Psi] \ \tilde{\gamma}$ we have

$$2S_{L_0}\left(\underline{\gamma} - \underline{\tilde{\gamma}}\right) < \left\|\underline{\gamma} - \underline{\tilde{\gamma}}\right\|_1.$$
(8)

Let j_i , i = 1, ..., 2N, be a permutation of the indexes 1, ..., 2N such that $j_1, ..., j_{L_0}$ are the indexes of the L_0 entries of $\underline{\gamma}$ with the largest absolute values. Then, from (8) we have

$$2\sum_{i=1}^{L_0} |\gamma_{j_i} - \tilde{\gamma}_{j_i}| < \sum_{i=1}^{L_0} |\gamma_{j_i} - \tilde{\gamma}_{j_i}| + \sum_{i=L_0+1}^{2N} |\tilde{\gamma}_{j_i}|$$
$$\sum_{i=1}^{L_0} |\gamma_{j_i} - \tilde{\gamma}_{j_i}| < \sum_{i=L_0+1}^{2N} |\tilde{\gamma}_{j_i}|$$
$$\sum_{i=1}^{L_0} (|\gamma_{j_i} - \tilde{\gamma}_{j_i}| + |\tilde{\gamma}_{j_i}|) < \sum_{i=1}^{L_0} |\tilde{\gamma}_{j_i}| + \sum_{i=L_0+1}^{2N} |\tilde{\gamma}_{j_i}|$$

and since

$$|\gamma_{j_i}| < |\gamma_{j_i} - \tilde{\gamma}_{j_i}| + |\tilde{\gamma}_{j_i}|$$

we get

$$\sum_{i=1}^{L_0} |\gamma_{j_i}| < \sum_{i=1}^{2N} |\tilde{\gamma}_{j_i}|$$

namely,

$$\left\|\underline{\gamma}\right\|_1 < \left\|\underline{\tilde{\gamma}}\right\|_1$$

so that (P_0) and (P_1) are equivalent.

Suppose (7) does not hold for some $\underline{x} \in \mathbb{R}^{2N}$ such that $[\Phi, \Psi] \underline{x} = 0$, namely, $2S_{L_0}(\underline{x}) \geq ||\underline{x}||_1$. Let us use, again, the permuted indexes $\{j_i\}_{i=1}^{2N}$ so that this time j_1, \ldots, j_{L_0} are the indexes of the L_0 entries of \underline{x} with the largest absolute values. Then choose γ so that

$$\gamma_{j_i} = \begin{cases} -2x_{j_i}, & \text{for } 1 \le i \le L_0\\ 0, & \text{otherwise} \end{cases}$$

and $\underline{\tilde{\gamma}} = \underline{\gamma} + \underline{x}$. Then, clearly, $\left\|\underline{\gamma}\right\|_1 = 2S_{L_0}(\underline{x})$ and $\left\|\underline{\tilde{\gamma}}\right\|_1 = \|\underline{x}\|_1$, so that

$$\left\|\underline{\gamma}\right\|_{1} \ge \left\|\underline{\tilde{\gamma}}\right\|_{1}$$

and since $\underline{\gamma} \neq \underline{\tilde{\gamma}}$, clearly, (P_0) and (P_1) are not equivalent, which completes the proof.

The next proposition is basically a reworded version of a similar result proven in [1]. However, we believe the proof here is somewhat more straightforward and provides the motivation for the main contribution of this note—a family of counterexamples which show that the bound in [1] is indeed tight.

Proposition 3: Let $L_0 < \frac{1}{M}$ be a given integer. Then, for all $\underline{x} \in \mathbb{R}^{2N}$ such that $[\Phi, \Psi] \underline{x} = 0$, we have

$$\Theta_{L_0}\left(\underline{x}\right) \le \left(\sqrt{2 + ML_0} - 1\right)^2 \tag{9}$$

where $\Theta_{L_0}(\underline{x})$ is as in (6).

Proof: Since $[\Phi, \Psi] \underline{x} = 0$, \underline{x} must be of the form

$$\underline{x} = \begin{bmatrix} I \\ A \end{bmatrix} \underline{v}$$

for some $\underline{v} \in \mathbb{R}^N$, where $A = -\Psi^T \Phi$ is also an orthogonal matrix. Let us now fix \underline{v} and let us denote $\underline{w} = A\underline{v}$. Swapping, if necessary, \underline{v} and \underline{w} , we may assume without loss of generality that among the L_0 largest (in absolute value) entries of \underline{x} , $m \ge \frac{L_0}{2}$ are the first m entries of \underline{v} , and the remaining $L_0 - m$ are entries of \underline{w} . Since, by its definition, $\Theta_{L_0}(\underline{\alpha}\underline{x}) = \Theta_{L_0}(\underline{x})$ for all $\alpha > 0$, we may assume that

$$\sum_{i=1}^{m} |v_i| = 1.$$
(10)

Let us denote

$$P = \sum_{i=m+1}^{N} |v_i|.$$

Observe that

$$\begin{aligned} \|\underline{w}\|_{\infty} &= \|A\underline{v}\|_{\infty} \\ &\leq \max_{1 \leq i, j \leq N} |A_{i,j}| \, \|\underline{v}\|_{1} = M \, \|\underline{v}\|_{1} \\ &\leq M \, (1+P) \,. \end{aligned}$$
(11)

Similarly, we can conclude that

$$\|\underline{v}\|_{\infty} \le M \|\underline{w}\|_{1}. \tag{12}$$

Since we assumed that the first *m* entries in \underline{v} are the largest, (10) implies that $||\underline{v}||_{\infty} \ge \frac{1}{m}$ and it follows from (12) that

$$\|\underline{w}\|_1 \ge \frac{1}{mM}.$$
(13)

Denoting $\theta = mM$, we have from (11) and (13)

$$\Theta_{L_{0}}(\underline{x}) = \frac{\sum_{i=1}^{m} |v_{i}| + S_{L_{0}-m}(\underline{w})}{\|\underline{v}\|_{1} + \|\underline{w}\|_{1}}$$

$$\leq \frac{1 + (L_{0} - m) \|\underline{w}\|_{\infty}}{\|\underline{v}\|_{1} + \|\underline{w}\|_{1}}$$

$$\leq \frac{1 + M (L_{0} - m) (1 + P)}{1 + P + \frac{1}{mM}}$$

$$\leq \frac{1 + (ML_{0} - \theta) (1 + P)}{1 + P + \theta^{-1}}.$$
(14)

Denoting the right-hand side of (14) by $f(\theta,P),$ we note that for $\frac{ML_0}{2} \leq \theta \leq ML_0$

$$\frac{\partial f\left(\theta,\,P\right)}{\partial P}=\frac{\theta^{-1}ML_{0}-2}{\left(1+P+\theta^{-1}\right)^{2}}\leq0$$

so

$$f(\theta, P) \leq \max_{\substack{ML_0 \\ 2 \leq \theta \leq ML_0}} \{f(\theta, 0)\}$$
$$\leq \max_{\substack{ML_0 \\ 2 \leq \theta \leq ML_0}} \left\{\frac{1 + ML_0 - \theta}{1 + \theta^{-1}}\right\}$$
$$= \left(\sqrt{2 + ML_0} - 1\right)^2.$$

Hence,

$$\Theta_{L_0}\left(\underline{x}\right) \le \left(\sqrt{2 + ML_0} - 1\right)^2.$$

Clearly, if $ML_0 < \sqrt{2} - 0.5$ then by this proposition

$$\Theta_{L_0}\left(\underline{x}\right) < \left(\sqrt{2 + \sqrt{2} - 0.5} - 1\right)^2 = \frac{1}{2}.$$

Hence, by Proposition 2, (P_0) and (P_1) are equivalent. This is a restatement of a result in [1].

Next we prove the following proposition.

Proposition 4: For every positive integer r, there exist orthogonal matrices $\Phi = [\phi_1 \cdots \phi_{2^{2r-1}}]$ and $\Psi = [\psi_1 \cdots \psi_{2^{2r-1}}]$ such that $|\phi_i^T \psi_j| \leq M \stackrel{\Delta}{=} 2^{-r+0.5}$ and a vector $\underline{x} \neq 0$ satisfying $[\Phi, \Psi] \underline{x} = 0$ so that $\Theta_{L_0}(\underline{x}) \geq \frac{1}{2}$ for all integers L_0 for which $\sqrt{2} - 0.5 \leq ML_0 \leq 1$.

Proof: We will prove the proposition by construction. Let r > 0 be any integer and we denote

$$m = 2^{r}$$

$$k = 2^{2r-1}$$

$$M = \frac{1}{\sqrt{k}}$$

$$L_{\max} = \frac{1}{M}$$

$$L_{\min} = \frac{\sqrt{2} - 0.5}{M}.$$
(15)

Furthermore, let

$$F^{(1)} = \begin{bmatrix} 1 & 1\\ 1 & -1 \end{bmatrix}$$
(16)

and

$$F^{(s)} = \underbrace{F^{(1)} \otimes \cdots \otimes F^{(1)}}_{s \text{ times}}$$
$$= F^{(1)} \otimes F^{(s-1)}$$
(17)

where \otimes denotes the Kronecker product (these matrices are known as the Hadamard matrices).

Now we choose

$$U = \frac{1}{\sqrt{k}} F^{(2r-1)}$$
 (18)

and

$$\underline{v} = \begin{bmatrix} \underline{1}_{m} \\ \underline{0}_{k-m} \end{bmatrix}$$
$$= \underline{e}_{1}^{\left(\frac{k}{m}\right)} \otimes \underline{1}_{m}$$
(19)

where $\underline{1}_m$ and $\underline{0}_{k-m}$ are *m*- and k - m-dimensional vectors of ones and zeros, respectively, $\underline{e}_1^{(\frac{k}{m})}$ is the first column of the $\frac{k}{m} = 2^{r-1}$ -dimensional identity vector. Then

$$U\underline{v} = \frac{1}{\sqrt{k}} \left(F^{\left(\frac{k}{m}\right)} \otimes F^{\left(m\right)} \right) \left(\underline{e}_{1}^{\left(\frac{k}{m}\right)} \otimes \underline{1}_{m} \right)$$
$$= \frac{1}{\sqrt{k}} \left(F^{\left(\frac{k}{m}\right)} \underline{e}_{1}^{\left(\frac{k}{m}\right)} \right) \otimes \left(F^{\left(m\right)} \underline{1}_{m} \right)$$
$$= \frac{m}{\sqrt{k}} \underline{1}_{\left(\frac{k}{m}\right)} \otimes \underline{e}_{1}^{\left(m\right)}.$$
(20)

Define

$$\underline{x} = \begin{bmatrix} \underline{v} \\ U\underline{v} \end{bmatrix}$$
(21)

then we observe from (19)–(21) that \underline{x} has a total of $m + \frac{k}{m}$ nonzero entries, m of which are equal to 1 and the remaining $\frac{k}{m} = 2^{r-1}$ are equal to $\frac{m}{\sqrt{k}} = \sqrt{2}$.

Hence, for any $L_{\min} \leq L_0 \leq L_{\max}$ (noting that $L_{\min} > 2^{r-1}$ and $L_{\max} < 2^r + 2^{r-1}$) we get

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$$\begin{aligned} u_{L_0}(\underline{x}) &= \frac{S_{L_0}(\underline{x})}{\|\underline{x}\|_1} \\ &= \frac{\frac{k}{m} \frac{m}{\sqrt{k}} + \left(L_0 - \frac{k}{m}\right)}{\frac{k}{m} \frac{m}{\sqrt{k}} + m} \\ &\geq \frac{2^{r-0.5} - 2^{r-1} + L_{\min}}{2^{r-0.5} + 2^r} \\ &= \frac{1}{2}. \end{aligned}$$

Namely, $\Phi = I$, $\Psi = -U$, and \underline{x} as defined in (21) constitute the required example which completes the proof of the proposition.

We can combine now the consequences of Propositions 3 and 4 and state our main result.

Theorem 5: (P_0) and (P_1) are guaranteed to be equivalent for any given two orthogonal matrices Φ , Ψ , and signal $\underline{S} = [\Phi, \Psi] \underline{\gamma}$ if and only if $M \|\gamma\|_0 \le \sqrt{2} - 0.5$.

III. CONCLUSION

Given a signal $\underline{S} \in \mathbb{R}^N$ one is interested in the sparsest representation of this signal in a given dictionary which consists of Φ and Ψ , two orthonormal bases in \mathbb{R}^N . This is an l_0 -optimization problem which is very difficult to solve. An alternative approach was proposed in [2], where it was shown that if the signal representation has no more than 0.5 (1 + 1/M) nonzero entries it can be found using an l_1 -optimization approach which leads to linear programming methods and is much simpler to solve. This bound was improved in [1] to become $(\sqrt{2} - 0.5)/M > 0.5 (1 + 1/M)$.

However, the question whether the bound is tight was left unanswered. We have established here that the Elad and Bruckstein bound is indeed tight.

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