# Group Discussion **Dual frames as Analysis operator**

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# Organization

- Introduction to analysis model.
- Basics of frame theory.
- Role of dual frames in sparse representation.
- Existing results on learning analysis operator.
- Dual frames as analysis operator.

#### Introduction of synthesis model

• Given a measurement vector  $y \in \mathbb{R}^m$  and its sensing matrix  $\Psi_{m \times d}$ , the problem of recovering  $x \in \mathbb{R}^d$  can be formulated the following way as finding the sparsest solution of linear equations  $y = \Psi x$ :

$$P_0: \min_{x} \|x\|_0$$
 subject to  $\Psi x = y$ .

• The convex relaxation of  $P_0$  problem can be posed as

$$P_1: \min_{x} \|x\|_1 \text{ subject to } \Psi x = y.$$

#### Introduction of analysis model

- Alongside synthesis, there is an analysis counterpart model.
- Let  $\Omega \in \mathbb{R}^{p \times d}$  be a signal transformation or an analysis operator. Its rows are the vectors  $(\omega_j)_{j=1}^p$  that will be applied to the signals.
- Applying  $\Omega$  to y, we obtain the (analysis) representation  $\Omega y$  of y. To capture various aspects of the information in y, we typically have  $p \geq d$ .

#### Definition

The co-sparsity  $\ell$  of a signal  $y \in \mathbb{R}^d$  with respect to  $\Omega \in \mathbb{R}^{p \times d}$  (or simply the co-sparsity of y) is defined to be:  $\ell := p - \|\Omega y\|_0$ .

- The index set of the zero entries of  $\Omega y$  is called the co-support of y.
- y is co-sparse when the co-sparsity of y is large, that is,  $\ell$  being close to p.

# Synthesis vs Analysis

- In the synthesis model, it is the columns  $\Psi_j, j \in T$ , associated with the index set T of nonzero coefficients that define the signal subspace. Removing columns from  $\Psi$  not in T leaves this subspace unchanged.
- In contrast, it is the rows  $\omega_j$  associated with the index set T' such that  $\langle \omega_j, y \rangle = 0, j \in T'$  that define the analysis subspace. In this case removing rows from  $\Omega$  for which  $\langle \omega_j, y \rangle \neq 0$  leaves the subspace unchanged.

## Basics of Frame Theory

#### Definition

A family of vectors  $(\psi_i)_{i=1}^n$  in  $\mathbb{R}^m$  is called a frame for  $\mathbb{R}^m$ , if there exists constants  $0 < A \le B < \infty$  such that

$$A \|x\|^{2} \leq \sum_{i=1}^{n} |\langle x, \psi_{i} \rangle|^{2} \leq B \|x\|^{2}, \forall x \in \mathbb{R}^{m}$$

- If A = B, then  $(\psi_i)_{i=1}^n$  is an A-tight frame.
- If A = B = 1, then it is a Parseval frame.
- If there exits a constant c such that  $\|\psi_i\| = c$  for all i = 1, 2, ..., n then  $(\psi_i)_{i=1}^n$  is an equal norm frame.
- If c = 1 then it is a unit-norm frame.

J. Cahill , P.G. Casazza , G. Kutyniok, "Operators and frames," Journal of Operator Theory, 2013

# Introduction to Frame Theory

#### Definition

Let  $\Psi = (\psi_i)_{i=1}^n$  be a frame in  $\mathbb{R}^m$ .

- The associated analysis operator  $T: \mathbb{R}^m \to \mathbb{R}^n$  is defined by  $Tx = \Psi^* x = (\langle x, \psi_i \rangle)_{i=1}^n, x \in \mathbb{R}^m$ .
- The associated synthesis operator is defined to be the adjoint operator  $T^*$ . A short computation shows that  $T^*: \mathbb{R}^n \to \mathbb{R}^m$  is given by  $T^*c = \Psi c = \sum_{i=1}^n c_i \psi_i, c = (c_i)_{i=1}^n \in \mathbb{R}^n$ .
- The associated frame operator is the map  $S: \mathbb{R}^m o \mathbb{R}^m$  defined to be

$$Sx = T^*Tx = \Psi \Psi^* x = \sum_{i=1}^n \langle x, \psi_i \rangle \psi_i, x \in \mathbb{R}^m.$$

## Role of dual frames in sparse representation

- A dual frame  $\Phi$  of  $\Psi$  provides a representation of a signal satisfying  $\Psi x = y$ , namely,  $x_{\Phi_v} = \Phi^* y$ .
- Is it possible to find a dual frame  $\Phi$  such that  $\Phi^*y$  is sparse?

$$D_0$$
: arg  $\min_{\Phi \in S_D} \|\Phi^* y\|_0$ 

- $S_D = \{ \Phi : \Psi \Phi^* = I \}$  is closed and convex.
- $I_1$  relaxation of  $D_0$ ,

$$D_1$$
: arg  $\min_{\Phi \in S_D} \|\Phi^* y\|_1$ 

## Relation between $P_0$ and $D_0$

- Let us define,  $S_{D_y} = \{\Phi^* y : \Phi \in S_D\}$  and  $S_{P_y} = \{x : \Psi x = y\}.$
- Claim:  $S_{D_v} = S_{P_v}$
- It is easily verifiable that  $S_{D_v} \subseteq S_{P_v}$ .
- Now it is enough to show that  $S_{P_{\nu}} \subseteq S_{D_{\nu}}$ .
- Let  $x \in S_{P_y}$ , then to show  $x \in S_{D_y}$ , that is  $x = \Phi_x^* y$  for some  $\Phi_x \in S_D$ .
- Let  $\Psi^+$  is canonical dual frame and  $x' = (\Psi^+)^* y$ . Now x' is a non-trivial solution of  $\Psi x = y$ .
- Then we have x = x' + z for some  $z \in \text{Null}(\Psi)$ .

# Relation between $P_0$ and $D_0$

- As  $y \neq 0$ , there exist i such that the i—th entry  $y_i$  of y is non-zero.
- Form a matrix  $(Z_y^x)_{n\times m}^*$  such that the i-th column is  $\frac{1}{y_i}z$  and all other columns are zero columns (note that selection of  $Z_y^x$  is not unique).
- $x = x' + z = (\Psi^+ + Z_y^x)^* y = (\Phi_Z)^* y$ , where  $\Phi_Z = \Psi^+ + Z_y^x$ .
- $\Psi \Phi_Z^* = I$  shows that  $\Phi_Z \in S_D$ .
- Therefore if  $\hat{\Phi}$  is the solution of  $D_0$  (respectively  $D_1$ ), then  $\hat{\Phi}^*y$  is the solution of  $P_0$  (respectively  $P_1$ ).

#### Continued ...

•  $\Phi_1, \Phi_2 \in S_D$  belongs to same equivalence class with respect to y if  $\Phi_1^* y = \Phi_2^* y$ .

#### Theorem

For a given system of equation  $\Psi x = y$ , let  $\hat{x}$  be an unique solution for  $P_0$  (respectively  $P_1$ ). Then there exist an unique solution  $\hat{\Phi}$  (up to equivalence) of  $D_0$ (respectively  $D_1$ ) such that  $\|\hat{x}\|_0 = \|\hat{\Phi}^*y\|_0$ (respectively  $\|\hat{x}\|_1 = \|\hat{\Phi}^*y\|_1$ ).

- Above theorem states that the properties like Restricted Isometry Property (RIP) and Null Space Property (NSP), which establish equivalence between  $P_0$  and  $P_1$ , also establish equivalence between  $D_0$  and  $D_1$ .
- Therefore, for a given y, it is possible to find a candidate  $\Phi$  from the set of dual frames of a good synthesis operator  $\Psi$ , so that  $\Phi^T$  acts as an analysis operator on y, that is, the co-sparsity of y with respect to  $\Phi^T$  becomes large, that is,  $\|\Phi^T y\|_0$  is small.

#### Learning analysis operator

- Let us consider a linear system  $\Psi X = Y$ .
- We can pose the following optimization problem to learn an analysis operator:

$$A_1$$
:  $\arg\min_{\Omega\in\mathcal{L}}\|\Omega y\|_1$ 

- To exclude trivial solutions,  $\Omega$  is to restricted to an admissible set  $\zeta$ .
- $\bullet$   $\zeta$  is taken as the set of unit norm tight frames.

M. Yaghoobi, S. Nam, R. Gribonval, and M. E. Davies, "ANALYSIS OPERATOR LEARNING FOR OVERCOMPLETE COSPARSE REPRESENTATIONS," 19th European Signal Processing Conference (EUSIPCO 2011)

# Sparse Bayesian Learning

- If we use SBL method on  $\Psi X = Y$ , then we can find a sparse  $X^*$ .
- We can find a dual frame  $\Psi_d$  corresponding to  $X^*$  via solving the following optimization:

$$F_0: \min_{\Psi_d} f(\Psi_d) \text{ subject to } \Psi \Psi_d^T = I, \quad \Psi_d^T Y = X^*,$$

where f is convex function of  $\Psi_d$ .

- Let  $\Psi_{d^*}$  be a dual frame such that  $\Psi_{d^*}^T Y = X^*$ .
- Let  $V = \text{span}\{Y\}$  and  $\dim(V) < m$ . Select (P d) vectors from  $V^{\perp}$ .
- Form an analysis operator  $\Omega_{P\times m}$  by concatenation of  $(\Psi_{d^*})_{i=1}^d$  and previously selected (P-d) vectors in any arbitrary order.

# Dual frame as analysis operator

- Let  $S \in \mathbb{R}^{m \times P}$  be a good synthesis operator.
- Take  $\zeta = \{S_d^T \in \mathbb{R}^{P \times m} : SS_d^T = I\}$ , that is,  $S_d$  is a dual frame of S.
- Assume SX = Y has a sparse solution, then there exist dual frame  $S_d$  of S such that  $S_d^T Y$  is sparse.
- Intuition: Consider a linear system SZ = Y. As S is a good synthesis operator then we can expect to recover a sparse  $Z^*$ . According to the previous discussion then we can have a dual frame  $S_{d^*}$  of S such that  $S_{d^*}^T Y = Z^*$ .

#### References

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- P. G. Casazza and G. Kutyniok, eds., "Finite frames: Theory and applications", Birkhauser Boston, Inc., Boston, MA, 2012.

#### Thank You