

# Greedy Pursuit Algorithms

Thomas Kealy

July 22, 2014

## OMP

---

**Algorithm 1:** Orthogonal Matching Pursuit

---

**input** : Observation vector  $\mathbf{y}$ , sensing matrix  $\mathbf{A}$ , stopping criterion  $s$   
initialization  
 $k \leftarrow 0$   
 $\Lambda_0 = \emptyset$   
 $\mathbf{r}_k \leftarrow \mathbf{y}$  ;  
**while**  $k \neq s$  *or*  $\mathbf{r}_k \neq 0$  **do**  
     $k \leftarrow k + 1$ ;  
     $\text{match}(h_k = A^T \mathbf{r}^{k-1})$ ;  
     $\Lambda_k = \Lambda_{k-1} \cup \arg \min_j h_k(j)$ ;  
    **update**::  
     $\hat{\mathbf{x}} \leftarrow \mathbf{A}_{\Lambda_k}^\dagger \mathbf{y}$ ;  
     $\mathbf{r}_k \leftarrow \mathbf{y} - \mathbf{A}_{\Lambda_k}^\dagger \mathbf{y}$   
**end**  
**output:**  $\hat{\mathbf{x}} = \arg \min_{x: \text{supp}(x) \subseteq \Lambda_k} \|\mathbf{y} - A\mathbf{x}\|_2$

---

OMP iteratively detects the support set of the signal - proceeding by extending the estimate by a single index per iteration. The algorithm uses a matched filter to find the column which is maximally correlated with the current estimate, and solves a least-squares problem to update the residual vector.

Remarks:

- The residual vector at step  $k$ ,  $\mathbf{r}_k$ , can be viewed as the orthogonalisation of the observation vector against the previously chosen columns of  $\mathbf{A}$ .