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Performance of Matching Algorithmsfor Signal Approximation

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Abstract: *One of the important classes of sparse signals isthe non-negative signals. Many algorithms have alreadybeenproposed to recover such non-negative representations, whereveravaricious and convex relaxed algorithms are among the mostpopular methods. The covetous techniques have been changedto incorporate the non-negativity of the depictions. Onesuch modification has been proposed for Extranious EquivalentDetection (EED), which first chooses positive constants and usesa non-negative optimization technique as a replacement for theorthogonal projection onto the nominated support. Which graduallybuilds the sparse representation of a signal by iterativelyadding the most correlated element of the lexicon, which iscalled an atom, to the set of selected elements. A disadvantageof ED is that the depiction found by the algorithm isnot the best representation using selected atoms. It may alsoreselect already selected atoms in the later iterations, whichslows down the junction of the algorithm. Asa result, we present a novel fast implementation of the Nonnegative EED, which is based on the QR decomposition and aniterative constants apprise. We will empirically show that such amodification can easily accelerate the implementation by a factorof ten in a reasonable size problem. We explain how the non-negativityconstraint of the coefficients stops us of using the canonical EED and how we can modify the algorithm to not onlyhave a more intuitive atom selection step, but have a lowercomputational complexity.*

Keywords: *Detection, decomposition, iteration, non-negative*

I. Introduction

The phrase compressed sensing refers to the problem of realizing a sparse input xusing few linear measurements that possess some incoherence properties. The fieldoriginated recently from an unfavorable opinion about the current signal compressionmethodology. The conventional scheme in signal processing, acquiring the entire signal and then compressing it, was questioned by Donoho [2].Indeed, this techniqueuses tremendous resources to acquire often very large signals, just to throw awayinformation during compression. The natural question then is whether we can combine these twoprocesses, and directly sense the signal or its essential parts using fewlinear measurements. Recent work in compressed sensing has answered this questionin positive, and the field continues to rapidly produce encouraging results.

The key objective in compressed sensing (also referred to as sparse signal recoveryor compressive sampling) is to reconstruct a signal accurately and efficiently from aset of few non-adaptive linear measurements. Signals in this context are vectors,many of which in the applications will represent images. Of course, linear algebraeasily shows that in general it is not possible to reconstruct an arbitrary signal froman incomplete set of linear measurements. Thus one must restrict the domain inwhich the signals belong. To this end, we consider sparse signals, those with fewnon-zero coordinates. It is now known that many signals such as real-world imagesor audio signals are sparse either in this sense, or with respect to a different basis.Since sparse signals lie in a lower dimensional space, one would think intuitivelythat they may be represented by few linear measurements.

This is indeed correct,but the difficulty is determining in which lower dimensional subspace such a signallies.Multicarrier modulation has regained interest over the last decade. Several all-digital variants have been proposed: discrete multitone (DMT) is adopted as transmission format for asymmetric digital subscriber line (ADSL) and presented as a candidate for very high bit rate digital subscriber line (VDSL); orthogonal frequency division multiplexing (OFDM) is proposed for wireless local area applications, e.g. HiperLAN. DMT schemes divide the bandwidth into parallel subbands or tones. The incoming bitstream is split into parallel streams that are used to QAM-modulate the different tones. The modulation is done by means of an inverse fast Fourier transform (IFFT). Before transmission of a DMT symbol, a cyclic prefix of samples is added. If the channel impulse response order is less than or equal to the cyclic prefix length v, demodulation can be implemented by means of an FFT, followed by a (complex) 1-tap frequency domain equalizer (FEQ) per tone to compensate for channel amplitude and phase effects.The challenges of building a classifier that can distinguish between high-dimensionalmembers of various classes based on their shape differences, involves devising a reliabledissimilarity measure that can perform shape-based comparisons of very high-dimensionalsignals.

Also, theautomation of the feature selection process to minimize human intervention and reliance on domain knowledge. Finally, a robust prototype-based classifier thatcan detect outliers in test data.In order to achieve the above objectives, a Matching Pursuits Dissimilarity Measureis presented. The EDDM extends the well-known signal approximation technique EquivalentDetections (ED) for signalcomparison purposes [1]. MP is a greedy algorithm thatapproximates a signal x as a linear combination of signals from a pre-defined dictionary.MP is commonly used for signal representation and compression, particularly image andvideo compression [5, 6]. The dictionary and coefficients information produced by the ED algorithm has been previously used in some classification applications. However, mostof these applications work on some underlying assumptions about the data and the MPdictionary (section 2.3). The EDDM is the first MP based comparison measure that doesnot require any assumptions about the problem domain. It is versatile enough to performshape-based comparisons of very high-dimensional signals and it can also be adoptedto perform magnitude-based comparisons, similar to the Euclidean Distance. Since the EDDM is a differentiable measure, it can be seamlessly used with existing clustering ordiscrimination algorithms.

Therefore, the EDDM may find application in a variety ofclassification and approximation problems of very high-dimensional signals, includingimage and video signals. The experimental results show that EDDM is more useful thanthe Euclidean distance for shape-based comparison between signals in high dimensions.

The potential usefulness of the MPDM for a variety of problems is demonstrated bydevising two important EDDM-based algorithms. The first algorithm, called CAMP, dealswith the prototype-based classification of high-dimensional signals. The second algorithmis called the EK-SVD algorithm and it automates the dictionary learning process for theMP approximation of signals.In the CAMP algorithm, EDDM is used with the Competitive Agglomeration (CA)clustering algorithm by Frigui and Krishnapuram to propose a probabilistic classificationmodel [2]. The CA algorithm is a fuzzy clustering algorithm that learns the optimal number of clusters duringtraining. Therefore, it eliminates the need for manually specifyingthe number of clusters beforehand. This algorithm has been named as CAMP as an abbreviation of CA and ED algorithms.

II. Non-Negative Least Squares Algorithm

Let A be am × n matrix and b be a vector of dimension m.Consider the following feasibility problem:

$Ax = b$ (1)

$x \geq 0$ (2)

A straightforward way of solving the above problem through linear programming isby solving the following LP problem:

(LP) : min Pnj=1 |sj|

$Ax + s = bx \geq 0$

Observe that this norm 1 minimization can be carried out very efficiently by thesimplex in most cases. However, there are some constraint matrices for which theSimplex method performs a large number of degenerate pivots, not improving thesolution for many iterations, leading to a poor performance. Our approach to solve the feasibility problem posed by relations 1 and 2 will alsobe the minimization of a p-norm, but different from the norm 1 considered in (LP),we will consider the norm 2, i.e., we will solve the following problem:

At first glance, problem (PLS) seems much harder than problem (LP). However,in cases where (LP) is highly degenerate (as pointed out before), it is usually simplerto solve (PLS).E. Barnes et al. in [6] showed that the normalized direction obtained by (PLS) isthe direction of the steepest ascent at $\pi 0$ on the dual polyhedron (D). This suggeststhat the dual direction obtained by (PLS) may be much better in practice than theone obtained by the linear update in (LP). E. Barnes et al. in [6] showed empiricallythat this is indeed true for some classes of problems.Since (PLS) is a convex program, KKT conditions are necessary and sufficient foroptimality. Thus, the vector (x, s) is asolution for P if and only if there exists π suchthat:

The NNLS algorithm starts with a primal feasible solution, i.e., one that is feasiblefor (PLS), and tries to find a solution for the problem (DLS). The NNLS algorithmis similar to the simplex method in the sense that we have a subset of the columnsof A that is a primal feasible basis, and then we move from one primal feasible basisto another. Unlike the simplex method, our 'basis' is not required to be square. Theonly requirement is that it is composed of linearly independent columns.Let B be a basis, i.e., a linearly independent subset of the columns of A. Thenone crucial step of the nonnegative least squares algorithm is to solve the followingproblem:

$\text{Min}\|Bx - bk2$

Since the columns of B are linearly independent, the solution will be:

$x = B+b$, where $B+ = (BtB)-1Bt$

The matrix B+ is called the generalized inverse or pseudo inverse. If B is a basis, wesay that it isfeasible for (PLS) if we have:

$x = B+b>0$

Theorem 1. Algorithm 1 terminates with a solution of problem (PLS).

1. Let B be the feasible basis for problem P
2. Let I_B be the index set of the columns in B
3. $\bar{x} \leftarrow B^{+}b$
4. $\pi \leftarrow b - B\bar{x}$
5. $S \leftarrow \{j : A_j > 0\}$
6. if $S = \phi$ the
7. stop: optimal solution found
8. end if
9. Let $k \in s$
10. $d \leftarrow B^{+}A_k$
11. $\theta \leftarrow \min_{d_j > 0} \frac{x_j}{d_j}$
12. $P \leftarrow I - BB^{+}$
13. $\theta \leftarrow \frac{\pi^t A_j}{\|PA_j\|^2}$
14. $\theta \leftarrow \min\{\theta, \bar{\theta}\}$
15. if $\theta = \bar{\theta}$ then
16. $I_B \leftarrow I_B \cup \{j\}$
17. if $\theta = \bar{\theta}$ then
18. $\bar{x}(\theta) \leftarrow \bar{x}_j - \theta d_j$
19. $I_B \leftarrow I_B - \{j : x(\theta) = 0\}$
20. end if
21. $B \leftarrow \lfloor A_j \rfloor, \forall_j \in I_B$
22. Return to 3
23. else
24. $I_B \leftarrow I_B \left\{ J : \theta = \frac{\bar{x}_j}{d_j} \right\}$
25. $B \leftarrow \lfloor A_j \rfloor, \forall_j \in I_B$
26. $\bar{x} \leftarrow B^{+}b$
27. Return to 10
28. end if

Proof. We will show that the algorithm terminates by showing that no basis can berepeated. Since the number of basis is finite, the result follows.In order to prove that no basis can be repeated, we will show that, if a basis B isupdated to Bˆ , then we must have:

$$\min_{x \geq 0} \|\hat{B}x - b\|^2 < \min_{x \geq 0} \|Bx - b\|^2$$

Let us suppose first that θ = θ ≤ θ

Let B be the current basis and Ajbe the entering column.Ifx is the current primal solution, then

x = (BtB)−1Btb

$$\min_{x\geq 0}\left\|\hat{B}x-b\right\|^2=\min_{x,t\geq 0}\left\|Bx+A_jt-b\right\|^2\leq\min_{x\geq 0}\left\|Bx-\left(b-A_j\theta\right)\right\|^2$$

Let Bˆ be the new basis. Then the solution of the last minimization problem is:

$$\bar{x}=\left(B^tB\right)^{-1}B^t\left(b-A_j\theta\right)=\bar{x}-\theta d$$

III. Extranious EquivalentDetection

One such greedy algorithm is Orthogonal Matching Pursuit (OMP), put forth byMallat and his collaborators (see e.g. [47]) and analyzed by Gilbert and Tropp [62].OMP uses subGaussian measurement matrices to reconstruct sparse signals. If Φis such a measurement matrix, then Φ ∗Φ is in a loose sense close to the identity.Therefore one would expect the largest coordinate of the observation vector y = Φ ∗Φxto correspond to a non-zero entry of x. Thus one coordinate for the support of thesignal x is estimated. Subtracting off that contribution from the observation vectory and repeating eventually yields the entire support of the signal x. OMP is quitefast, both in theory and in practice, but its guarantees are not as strong as those ofBasis Pursuit.

The OMP algorithm can thus be described as follows:

Orthogonal Matching Pursuit (OMP)

Input: Measurement matrix Φ, measurement vector u = Φx, sparsity level s

Output: Index set I ⊂ {1, d}

Procedure:

Initialize Let the index set I = ∅ and the residual r = u.

Repeat the following s times:

Identify Select the largest coordinate λ of y = Φ ∗r in absolute value. Break ties lexicographically.

Update Add the coordinate λ to the index set: I ← I ∪ {λ}, and update the residual:

xˆ = argmin

z

k u − Φ| Izk 2; r = u − Φˆx.

Once the support I of the signal x is found, the estimate can be reconstructed asxˆ = Φ †Iu, whererecall we define the pseudoinverse by Φ †I def= (Φ ∗IΦI) −1Φ ∗I.The algorithm's simplicity enables a fast runtime. The algorithm iterates s times,and each iteration does a selection through d elements, multiplies by Φ ∗, and solvesa least squares problem. The selection can easily be done in O(d) time, and themultiplication of Φ ∗ in the general case takes O(md). When Φ is an unstructuredmatrix, the cost of solving the least squares problem is O(s2d). However, maintaininga QR-Factorization of Φ| I and using the modified Gram-Schmidt algorithm reducesthis time to O(| I| d) at each iteration. Using this method, the overall cost of OMPbecomes O(smd). In the case where the measurement matrix Φ is structured with afast-multiply, this can clearly be improved.

IV. Stagewise Extranious EquivalentDetection

An alternative greedy approach, StagewiseOrthogonal Matching Pursuit (StOMP)developed and analyzed by Donoho and his collaborators [23], uses ideas inspired bywireless communications. As in OMP, StOMP utilizes the observation vector y = Φ ∗uwhere u = Φx is the measurement vector. However, instead of simply selecting thelargest component of the vector y, it selects all of the coordinates whose values areabove a specified threshold. It then solves a least-squares problem to update theresidual. The algorithm iterates through only a fixed number of stages and thenterminates, whereas OMP requires s iterations where s is the sparsity level.

The pseudo-code for StOMP can thus be described by the following.

Input: Measurement matrix Φ, measurement vector u = Φx,

Output: Estimate ˆx to the signal x

Procedure: Initialize Let the index set I = ∅, the estimate ˆx = 0, and the residual r = u.Repeat the following until stopping condition holds:

Identify Using the observation vector y = Φ ∗r, setJ = {j : | yj| >tkσk},where σk is a formal noise level and tk is a threshold parameter for iterationk.

Update Add the set J to the index set: I ← I ∪ J, and update the residual and estimate:xˆ| I = (Φ ∗IΦI) −1Φ ∗Iu, r = u − Φˆx.

The thresholding strategy is designed so that many terms enter at each stage, and so that algorithm halts after a fixed number of iterations. The formal noise level σk is proportional the Euclidean norm of the residual at that iteration.

Syphilis antigen in a bloodsample. Since this test was expensive, the method was to sample a group of mentogether and test the entire pool of blood samples. If the pool did not contain theantigen, then one test replaced many. If it was found, then the process could eitherbe repeated with that group, or each individual in the group could then be tested.These sublinear algorithms in compressed sensing use this same idea to test for elements of the support of the signal x. Chaining pursuit, for example, uses a measurement matrixconsisting of a row tensor product of a bit test matrix and anisolation matrix, both of which are 0-1 matrices. Chaining pursuit first uses bit teststo locate the positions of the large components of the signal x and estimate thosevalues. Then the algorithm retains a portion of the coordinates that are largestmagnitude and repeats. In the end, those coordinates which appeared throughouta large portion of the iterations are kept, and the signal is estimated using these.Pseudo-code is available in [3], where the following result is proved.

Theorem (Chaining pursuit [31]). With probability at least $1 - O(d^{-3})$, the$O(s \log^2 d) \times d$ random measurement operator Φ has the following property. For$x \in \mathbb{R}^d$ and its measurements $u = \Phi x$, the Chaining Pursuit algorithm produces asignal $\hat{x}$ with at most s nonzero entries. The output $\hat{x}$ satisfies

$$\|x - \hat{x}\|_1 \leq C(1 + \log s)\|x - x_s\|_1.$$

The time cost of the algorithm is $O(s \log^2 s \log^2 d)$.HHS Pursuit, a similar algorithm but with improved guarantees, uses a measurement matrix that consists again of two parts. The first part is an identificationmatrix, and the second is an estimation matrix. As the names suggest, the identification matrix is used to identify the location of the large components of the signal,whereas the estimation matrix is used to estimate the values at those locations. Eachof these matrices consist of smaller parts, some deterministic and some random. Using this measurement matrix to locate large components and estimate their values, HHS Pursuit then adds the new estimate to the previous, and prunes it relative tothe sparsity level.

This estimation is itself then sampled, and the residual of thesignal is updated. Let $x \in \mathbb{R}^d$ and let $u = \Phi x$ be the measurement vector.The HHS Pursuit algorithm produces a signal approximation $\hat{x}$ with $O(s/\varepsilon^2)$ nonzeroentries. $\|x - \hat{x}\|_2 \leq \sqrt{\varepsilon}\|x - x_s\|_1$,where again x_s denotes the vector consisting of the s largest entries in magnitudeof x. The number of measurements m is proportional to $(s/\varepsilon^2)\,\mathrm{polylog}(d/\varepsilon)$, andHHS Pursuit runs in time $(s^2/\varepsilon^4)\mathrm{polylog}(d/\varepsilon)$. The algorithm uses working space$(s/\varepsilon^2)\mathrm{polylog}(d/\varepsilon)$, including storage of the matrix Φ.

There are other algorithms such as the Sudocodes algorithm that as of now onlywork in the noiseless, strictly sparse case. However, these are still interesting becauseof the simplicity of the algorithm. The Sudocodes algorithm is a simple two-phasealgorithm. In the first phase, an easily implemented avalanche bit testing schemes applied iteratively to recover most of the coordinates of the signal x. At thispoint, it remains to reconstruct an extremely low dimensional signal (one whosecoordinates are only those that remain). In the second phase, this part of the signalis reconstructed, which completes the reconstruction. Since the recovery is twophase, the measurement matrix is as well. For the first phase, it must contain asparse submatrix, one consisting of many zeros and few ones in each row. For thesecond phase, it also contains a matrix whose small submatrices are invertible. Thefollowing result for strictly sparse signals.Combinatorial algorithms such as HHS pursuit provide sublinear timerecovery withoptimal error bounds and optimal number of measurements. Some of these arestraightforward and easy to implement, and others require complicated structures.The majordisadvantage however is the structural requirement on the measurementmatrices. Not only do these methods only work with one particular kind of measurement matrix, but that matrix is highly structured which limits its use in practice.There are no known sublinear methods in compressed sensing that allow for unstructured or generic measurement matrices

V. Outputs

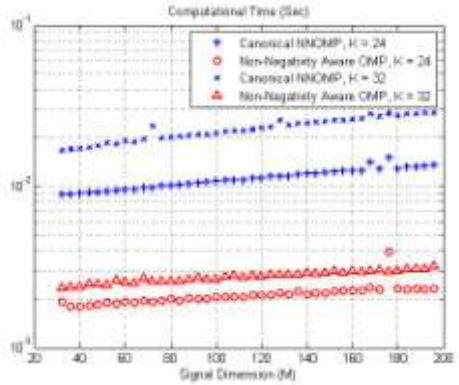

Fig 1 Computation time for the fixed N = 256 and K = 24 & 32

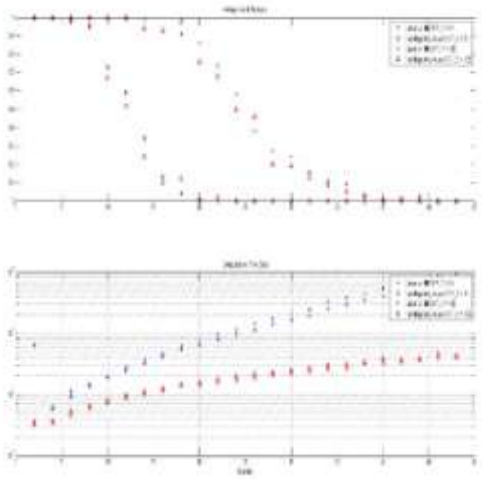

Fig 2: Average exact recovery and Computational time(sec)

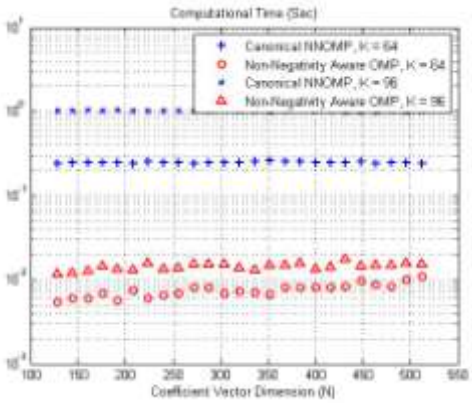

Fig. 3. Computation time for the fixed M = 128 and K = 64 & 96

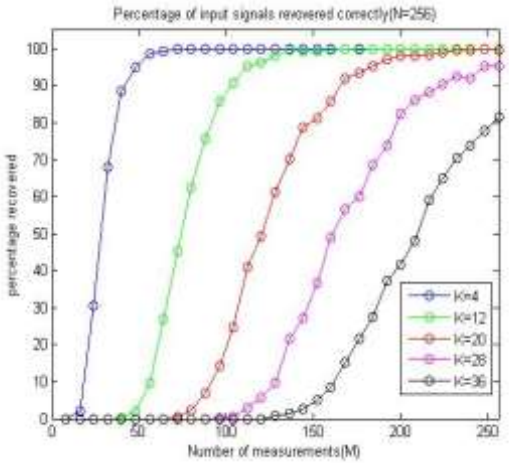

Fig 4: Percentage of recovered signals

Fig 5: Sparse AOMP data

VI. Concusion

A matching pursuits dissimilarity measure has been presented, which is capableof performing accurate shape-based comparisons between high-dimensional data. Itextends the matching pursuits signal approximation technique and uses its dictionaryand coefficient information to compare two signals. AOMP is capable of performingshape-based comparisons of very high dimensional data and it can also be adapted toperform magnitude-based comparisons, similar to the Euclidean distance. Since AOMP is a differentiable measure, it can be seamlessly integrated with existing clusteringor discrimination algorithms. Therefore, AOMP may find application in a variety ofclassification and approximation problems of very high dimensional data.The AOMP is used to develop an automated dictionary learning algorithm for MPapproximation of signals, called Enhanced K-SVD. The EK-SVD algorithm uses theAOMP and the CA clustering algorithm to learn the required number of dictionaryelements during training. Under-utilized and replicated dictionary elements are graduallypruned to produce a compact dictionary, without compromising its approximationcapabilities. The experimental results show that the size of the dictionary learned by ourmethod is 60% smaller but with same approximation capabilities as the existing dictionarylearning algorithms.The AOMP is also used with the competitive agglomeration fuzzy clustering algorithm to build aprototype-based classifier called AMP. The AMP algorithm buildsrobust shape-based prototypes for each class and assigns a confidence to a test patternbased on its dissimilarity to the prototypes of all classes. If a test pattern is different fromall the prototypes, it will be assigned a low confidence value. Therefore, our experimentalresults show that the CAMP algorithm is able to identify outliers in the given test databetter than discrimination-based classifiers, like, multilayer and support vectormachines.We presented a new greedy technique based on OMP,suitable for non-negative sparserepresentation, which is muchfaster than the state of the art algorithm. The new algorithm hasa slightly different atom selection procedure, which guaranteesthe non-negativity of the signal approximations. Although theselection step is more involved, the overall algorithm has amuch faster implementation. The reason is that with the newselection procedure, we can use fast QR implementation of theOMP. The computational complexity of two NNOMP's wererederived and the differences were demonstrated.

The experimental resultsshow that the size of the dictionary learned by our method is 60% smaller but with sameapproximation capabilities as the existing dictionary learning algorithms.

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